Hybrid Model for Short-Term Forecasting in Electric Power System

Victor Kutbatsky, Denis Sidorov, Nikita Tomin and Vadim Spiryaev

***Abstract*— The novel hybrid model for forecasting of time series characterized by nonlinear, nonstationary behavior is presented. Experimental studies on synthetic and real data are carried out and discussed. The application of developed approach for forecasting of price situation in the electricity market and for forecasting of the parameters of the expected operation conditions of the electric power system has demonstrated the accuracy improvement using the most common metrics. The system is examined using the benchmark data records from Australian national electricity market.**

***Index Terms*— Hilbert-Huang Transform; artificial neural networks; forecasting; electricity price; power systems.**

I. Introduction

Development of the state-of-the-art technique for robust forecasting of behavior of nonlinear and nonstationary power systems is one of the challenges in energetics. In this paper we summarize the results of experimental studies on the performance of the intelligent[1] hybrid system in two areas:

- forecasting of price situation in the competitive electricity market,
- forecasting of the parameters of the expected operation conditions of the electric power system (EPS).

Development of systems and devices for monitoring the state of energy and electrical equipment (devices and systems of diagnostics) and also monitoring the EPS operation conditions appears to be highly important because of radically changed development trends and complicated operating conditions of large-scale Interconnected Power Systems [1, 2].

The key condition for reliable work of EPS is the presence of efficient system forecasting of operation parameters (load flows, power flow, voltage magnitude, etc) and process characteristics (power and electricity losses, prices, etc). Most of the works emphasize that the highest accuracy of the state parameters forecasting can be obtained on the basis of artificial neural networks (ANN) models. In the cases when state variables are rather variable and nonstationary it is more sensible to use the neural network based intelligent models.

This paper presents the experimental studies of using the hybrid model for the short-term forecasting the parameters of expected operating conditions and electricity prices.

The paper is organized as follows. We outline the problem statement in Sections II and III. The review of the state of the art models for the short-term forecasting is presented in Section IV. In Section V we propose the novel hybrid model for nonstationary time series forecasting. The results of experimental studies of electricity price forecasting (EPF) as well as forecasting the parameters of the expected operation conditions of power systems are presented and discussed in Section VI.

II. Problem Statement

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.

Qualitative forecasting of frequency is an important optimization parameter of system-wide management of the electric network. 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, noisy input data, etc.

Forecasting the voltage magnitude is necessary because during the state estimation procedure current state is estimated with some delay, while monitoring and control problems require some advance estimation of system state ("to control is to foresee") [3].

Forecast of active power flows is necessary for determination of margins transfer capabilities of ties in the expected operating 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.

Time sequence of individual stages of monitoring, forecasting and control of operating conditions is shown in Fig.1.

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[1] The term "intelligent" is used in reference to the approaches, methods, systems and complexes using artificial intelligence technologies

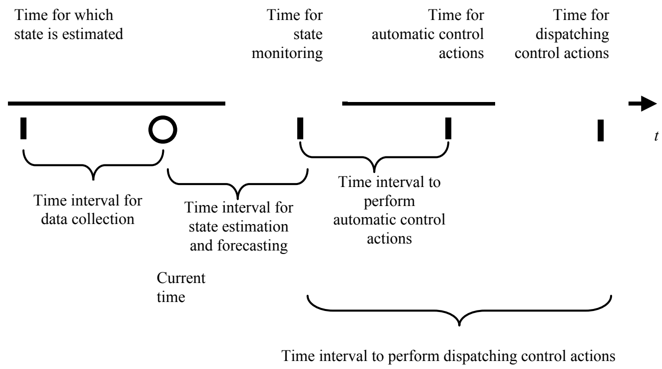

Fig. 1. Time diagram of events in the system for monitoring, forecasting and control in EPS.

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 to improve the coordination of the control stages, means and systems.

One of the key conditions for a successful activity of electricity market participants in the free trade sector is consideration for the price situation in the market while preparing the bids for electricity purchase and/or sale.

With the total liberalization of the wholesale electricity market the dynamic of change in the spot price will be determined by trade strategy, experience and qualification in the field of management of risks, and acceptable level of risks as well as by how the generation company will balance the potentially profitable but volatile possibilities of selling at spot prices and a desire to hedge the risk and retain the profit at a stable level of profitability. It should be noted that all other conditions being equal a large share of electricity sales in the forward market at fixed prices supposes a lower level of business risk. This provides generation companies with an acceptable level of profitability to maintain credit capacity of the company provided the generation costs remain fixed. Currently generation companies can hedge the risk of price volatility by unregulated forward contracts at fixed price. Further to expand the possibilities of hedging power industry the exchanges can involve other financial instruments, for example, futures.

III. Features Parameters of EPS and Electricity Price Time Series

Two important forecasting topics that are currently getting the attention in EPSs are addressed in this paper: parameters of EPS and electricity prices. Each of these time series exhibits its own features.

A. *Parameters of Electric Power System*

Parameters of operating condition in power systems are very nonstationary.

Power deviations from the average value for one transmission line (TL) are ± 200 MW at the limiting transmitted power 750 MW (fig. 2). It is noted, that power deviations are associated not only with change of load power, but also with restriction on the regulate power of units electric stations.

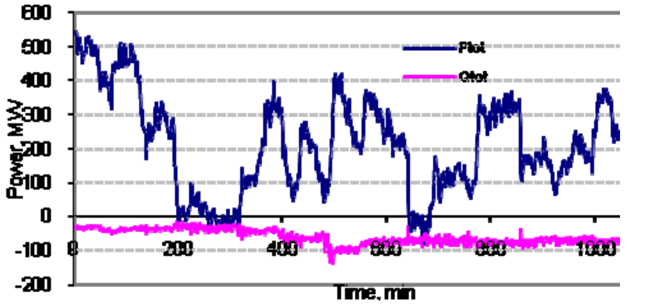

Fig.2. Change in exchange power of one TL 500 kV.

To estimate the dynamics of frequency variation the frequency measurements were carried out in Irkutsk EPS during the 4 days. The frequency deviations are shown in Fig.3. Most of the deviations were within the limits ± 20 mHz.

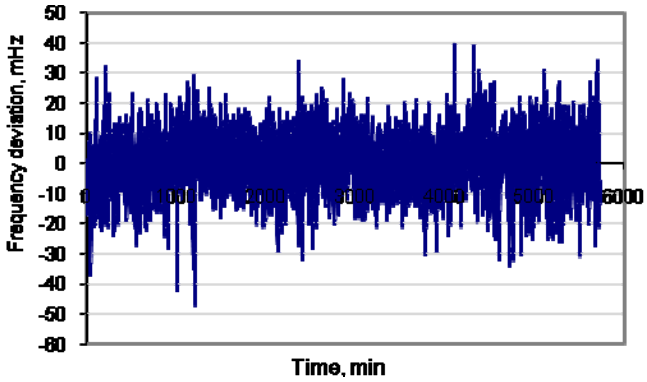

Fig. 3. Frequency deviation with «1 minute » averaging period.

B. *Electricity Prices*

Electricity price time series on a deregulated electricity markets are generally considered as erratic and ill-behaved [4, 5]. Analysis of competitive market operation is indicative of the fact that electricity prices depend on weather and seasonal factors, volume of consumption, mix and characteristics of generation equipment, price strategies of market participants, topology of networks, constraints on transfer capability of controlled cut-sets and other factors. In particular seasonal temperature fluctuations explains essentially the fluctuations in electricity consumption and as a result – fluctuations in prices.

The tendency of electricity price change in time can be characterized using the statistical index volatility σ:

$$\sigma=\left(\ln\left(\frac{P_i}{P_{i-1}}\right)-\frac{\sum_{i=1}^{N}\ln\left(\frac{P_i}{P_{i-1}}\right)}{n-1}\right)\sqrt{\frac{m}{n}} \qquad (1)$$

where m is the number of periods of certain duration for the workdays of a year; n is quantity of days; P_i , P_{i-1} are price values during current and previous time instants, respectively.

The volatility is characterized by so called clusterization, i.e. the presence of a large number of price peaks in some time intervals and rather calm price behavior in the other ones. Table I presents the results of volatility analysis for competitive electricity markets in Europe and Russia before May 2007 and May 2008.

TABLE I. DATA ON VOLATILITY OF COMPETITIVE ELECTRICITY MARKETS IN EUROPEAN COUNTRIES AND IN RUSSIA

Competitive market		Weighted average monthly price, Euro/MW*h		Volatility, %	
		May		*May*	
		2007	*2008*	*2007*	*2008*
European countries	Nord Pool	37,8	41.4	77	81
	GME	68,2	69.1	42	44
	EEX	33,9	32.6	94	91
	OMEL	49,4	33.1	78	80
	Powernext	32,1	43.1	90	92
	APX NL	41,7	44.3	91	93
Russia	ATS – European part	17,0	19.1	2	4
	ATS – Siberia	14,3	15.3	6	7

The use of an efficient EPF systems becomes a competitive advantage for the market participants. The results of EPFs are very useful for the transmission company for a variety of purposes: to schedule short-term generator outage, design load response programs, to name a few. They can also be used by generation companies to bid into the market strategically as well as to optimally manage its assets. Price forecasting plays an important role in power system planning and operation, risk assessment and in other decision making [6-9].

IV. REVIEW OF THE SHORT-TERM FORECASTING MODELS

The state of the art short-term forecasting technologies employ the following models:

- AutoRegressive Integrated Moving Average, ARIMA,
- Generalized AutoRegressive Conditional Heteroskedasticity, GARCH,
- Fourier spectral analysis.

As part of artificial neural networks [10] the most common models:

- multilayer perceptron, MLP (Fig.4),
- radial basis function network, RBF.

Recently Support Vector Machine (SVM) appears to be one of the most promising technologies [11].

A. Artificial Neural Networks Models

An intelligent approach based on the artificial neural network (ANN) for short-term forecasting of the nonstationary operating conditions has been proposed in [12].

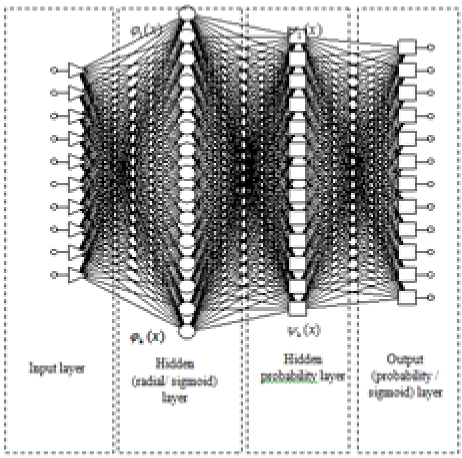

Fig. 4. The generalized multi-layer perceptron structure.

The approach is implemented in the subsystem of the intelligent software ANAPRO (Fig. 5, blocks 1-4) [13, 14].

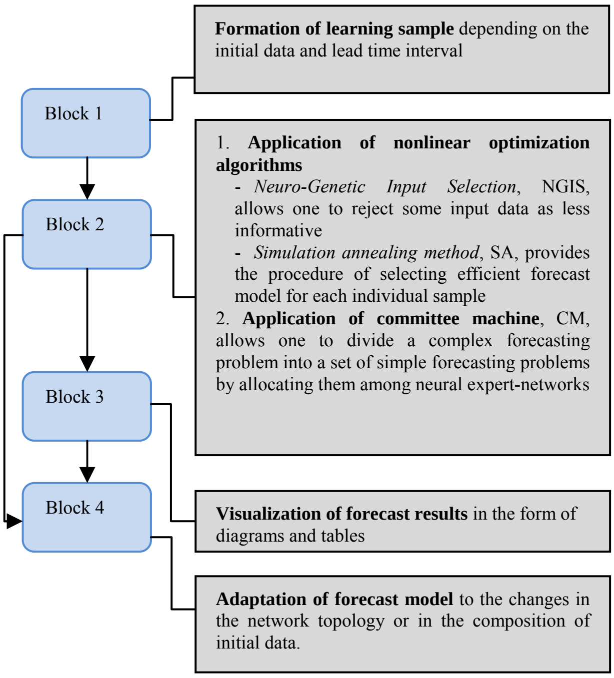

Fig.5. Forecast subsystem of the ANAPRO software.

The use of nonlinear optimization algorithms, namely, the methods of simulated annealing (SA) and neuro-genetic input selection (NGIS) [11], provides the procedure of choosing the best forecasting model for each individual sampling period.

In the neural network forecasting the ANN structures themselves are the intelligent models. Each iteration of the SA algorithm represents an ANN of a certain type and architecture. The ANN type can be repeated but network architecture will always be different. According to the chosen criterion the iteration algorithm makes a search for the optimal ANN structure (see Fig.6). With changes in the network topology or input data, including also the factors that affect the forecasted parameters the algorithm envisages adaptation of the forecasting model.

It is to be noted that the SA algorithm can select a neural network model for which the input parameters will be the most significant.

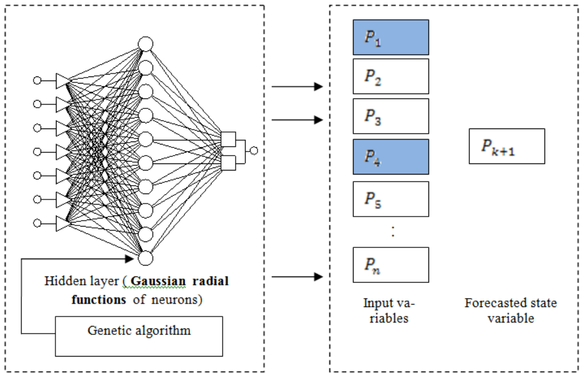

Fig. 6. Neural-genetic selection diagram.

Experimental computations [15] have indicated a rather high accuracy forecasting based on intelligent neural approach in comparison with the regression models, and with traditional neural network forecasting. But these calculations have shown that intelligent model is not very good "at guessing" the peak zones. It is to be noted that forecasting of the peaks is one of the main challenges.

B. Hilbert-Huang Transform

Recently, nonlinear and nonstationary analysis techniques based on the Hilbert-Huang Transform (HHT) [16] have been employed for short-term forecasting [17-19].

In order to increase the accuracy of the operation conditions forecasting the "intelligent" neural approach has been developed at the Energy Systems Institute SB RAS. This approach is based on both neural network technologies and HHT.

The Hilbert-Huang transform consists of two parts:

- Empirical mode decomposition (EMD) [20];
- Hilbert transform (HT).

C. Empirical mode decomposition

The data flow diagram is presented in Fig. 7. According to EMD, the signal x(t) is supposed to be decomposed into special orthogonal 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 be congruent;
- the median value of envelopes which are determined by local maxima and minima are supposed to be zeros for intrinsic mode functions at any point.

In contrast to standard methods of time series processing, the method of IMFs construction starts with the highest frequency component, and the last extracted function is usually monotone, or has only one extreme.

EMD can decompose the time series into different IMFs, These IMF are much more regular. It makes it possible to see periodical components, stochastic component and trends.

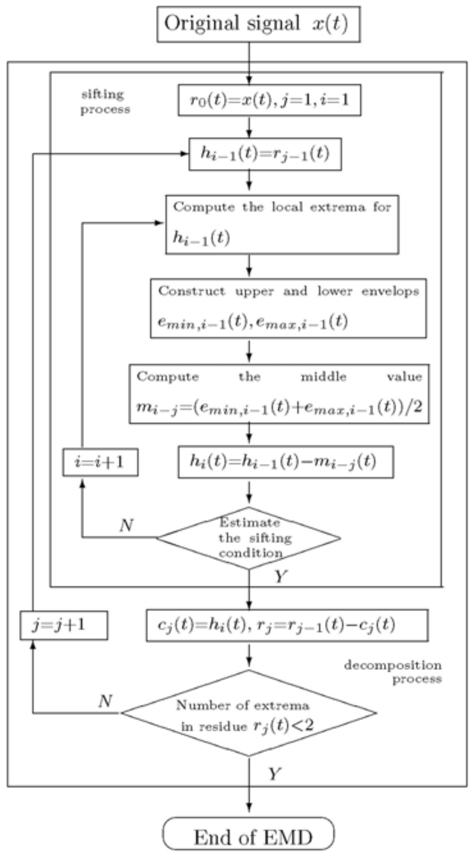

Fig. 7.The algorithm of the empirical mode decomposition.

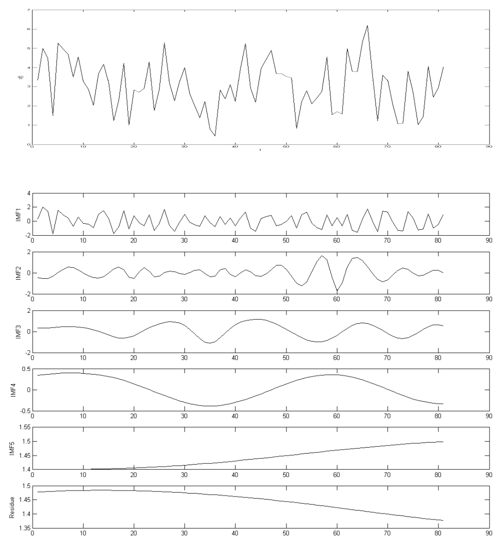

Fig. 8. Input signal $x(t)$ (top).Set of IMF's $x(t)$ (bottom).

Fig. 8 demonstrates the decomposition of the certain nonstrationary signal *x(t)*.

Thus, at the end of decomposition process, the original signal can be presented as follows:

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

$$=\sum_{i=1}^{q} c_i(t)+\sum_{j=q+1}^{p} c_j(t)+\sum_{k=p+1}^{n} c_k(t)+r_n(t), \quad (2)$$

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.

It is to be noted that for the majority of analyzed time series, the requested number of IMF is less than 10.

B. 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*.

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

$$z(t) = x(t) + ix_H(t), \tag{3}$$

where $ix_H(t)$ is the Hilbert transform of $x(t)$ obtained from

$$x_H(t) = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{x(s)}{t-s} ds. \tag{4}$$

In (4) PV stands for the Cauchy principal value of the integral. We can rewrite (3) in an exponential form

$$z(t) = A(t)e^{i\psi(t)}, \tag{5}$$

where

$$A(t) = \sqrt{x^2(t) + x_H^2(t)}, \tag{6}$$

and

$$\psi(t) = arctg \frac{x_H(t)}{x(t)}. \tag{7}$$

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

$$\omega(t) = \dot{\psi}(t) = \frac{d}{dt} arctg \frac{x_H(t)}{x(t)}. \tag{8}$$

V. The Hybrid HHT and ANN Model for Forecasting of Short-Term Operation Conditions

In the cases where parameters are rather variable and nonstationary it is more sensible to employ the intelligent hybrid model based on the combination of ANN models and HHT – hybrid (HHT-ANN) model [21-25].

The use of hybrid model or combination of several models has become a common practice to improve the forecasting accuracy, since the well-known M-competition [24] where the combination of forecasts from more than one model often improves the whole forecasting procedure. The basic idea of combining the forecasting models is to use each model unique feature to capture different patterns in the data. Based on both theoretical and empirical findings we can see that the combination of different methods can be an efficient way to improve forecasts [25-27]. However, combination of the proposed techniques in the framework of the hybrid forecast method and especially its application for expected operating conditions can be considered as the contribution of the paper.

Let us consider now the hybrid (HHT-ANN) model for short-term forecast of parameters of expected operating conditions based on the two-stage adaptive neural network approach. The first stage involves decomposition of the time series into intrinsic modal functions and subsequent application of the Hilbert transform. At the second stage the computed modal functions and amplitudes are employed as input functions for artificial neural networks.

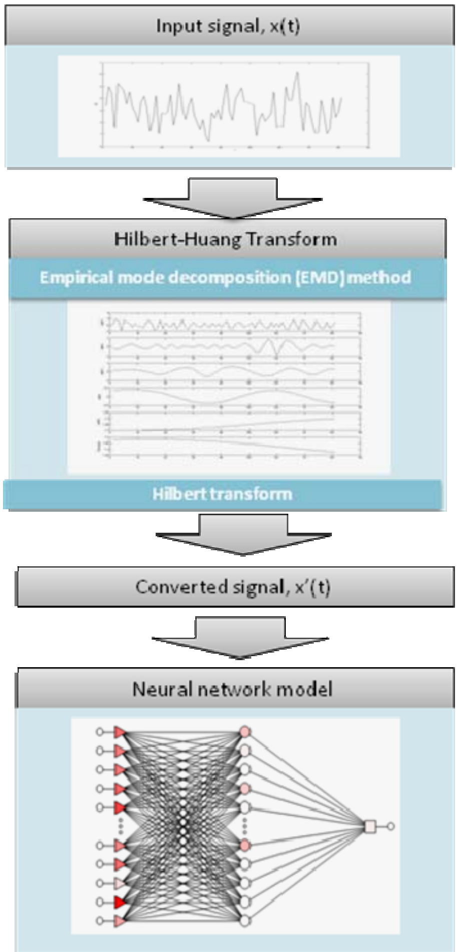

Fig. 9. Hybrid model construction.

Let us outline the key stages of our intelligent hybrid model construction based on the HHT and ANN technologies (Fig.9):

A. The EMD algorithm is used to decompose the initial non-stationary signal $x(t)$ into the several IMFs. Following the Hilbert transform the corresponding instantaneous amplitude (A) and instantaneous frequency are calculated.
B. The calculated values of IMFs and As are used as input values for neural network model.
C. The algorithms of neural-genetic selection and simulated annealing are used to construct the neural network model. This ANN model is learned to forecast the corresponding changes of EPS parameters on a given interval of expectation.

VI. Experimental Studies

In order to evaluate the accuracy of short-term forecasting the following metrics were employed:

- Mean absolute percentage error (MAPE):
-

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{\left|x_i - \bar{x}_i\right|}{x_i} \cdot 100\%,$$

- Mean absolute error (MAE metric):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|x_t - \overline{x_t}\right|;$$

- *Root mean squared error* (RMSE metric):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \overline{x_t})^2}\ ,$$

where $\overline{x_i}$ are forecast values of parameter; x_i are actual values of parameter under forecasting; n is lead time interval.

A. The short-term EPF

In the paper [15], [28] an intelligent approach based on the neural network technologies to EPF for different lead time intervals has been proposed. This approach has demonstrated good results in comparison with traditional neural network forecasting [6]. This approach allows an efficient solution of forecasting problems under strict requirements for accuracy of such calculations and under considerable nonstationarity of the parameters studied. In this paper to compare the effectiveness of the models for hourly forecasts based on intelligent hybrid approach – hybrid model and the intelligent neural network model.

The calculations of EPF were based on the intelligent software ANAPRO.

The proposed hybrid HHT-ANN model [22] was used to make hourly forecasts of spot electricity prices for two European price zones for different time intervals. For this purpose the studied time series was decomposed into IMFs by the Huang method, and the Hilbert integral transform to obtain the amplitudes, *A*. The latter along with IMFs were used as input values of the selected neural network model.

In the work the developed intelligent hybrid approach was used to forecast nodal and spot electricity prices for two price zones for different time intervals:

- Hourly "a fortnight ahead",
- Average daily "a day ahead".

I. A day-ahead electricity price forecast

Initial time series were represented by the arrays of average daily electricity price values for Price zone 1 over the period 22.10.2007 – 05.11.2008.

Along with the retrospective values of electricity prices the following parameters and characteristics were used in calculations:

- Power flows;
- Basic and peak electricity values in the adjacent zones;
- Inflow;
- Precipitation;
- Air temperature.

To make a short-term forecast of the parameter the SA procedure was used to create an GRNN-type neural network - hybrid model. Its input layer contained nine IMFs and the values of amplitudes $A_i, i = \overline{1,9}$ and the dependent characteristics. As a result of learning the NGIS algorithm excluded IMF1 and "Inflow" from the input layer.

The results are illustrated in Fig. 10 and presented in Table II show that the hybrid HHT-ANN model provides the best forecast accuracy.

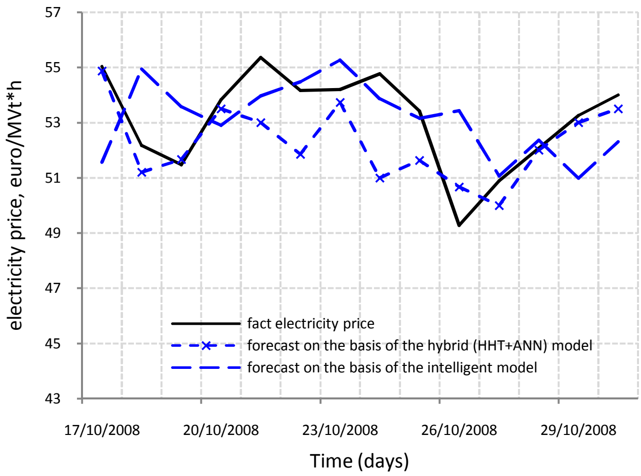

Fig. 10. Result of the days electricity prices forecasting with a lead time interval of 2 week on the basis of different models.

TABLE II. RESULT OF THE DAYS ELECTRICITY PRICES FORECASTING WITH A LEAD TIME INTERVAL OF 2 WEEK ON THE BASIS OF DIFFERENT MODELS.

Days	Error, %		Days	Error, %	
	HHT+ANN	ANN		HHT+ANN	ANN
17.10.08	0.29	6.29	24.10.08	6.88	1.66
18.10.08	1.86	5.31	25.10.08	3.35	0.49
19.10.08	0.39	4.08	26.10.08	2.82	8.42
20.10.08	0.61	1.73	27.10.08	1.75	0.33
21.10.08	4.26	2.51	28.10.08	0.13	0.58
22.10.08	4.25	0.59	29.10.08	0.49	4.26
23.10.08	0.85	1.97	30.10.08	0.93	3.13
MAPE, %				**2.06**	**2.95**

II. Hourly "a one day ahead"

The array of the learning sample included 2184 hours measurements (3 months) of spot electricity prices. To make the short-term forecast of the parameter the SA procedure was used to create an RBF-type neural network - hybrid model. Its input layer contained nine IMFs and the values of amplitudes $A_i, i = \overline{1,9}$ As a result of learning the NGIS algorithm excluded IMF1 and $A_i, i = \overline{1,3}$ from the input layer.

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 (see Table III) was made to assess the forecast quality.

The results of computation of the EPFs are presented in Fig. 11 and in Table III. It demonstrates that HHT-ANN hybrid model provides the best forecast accuracy.

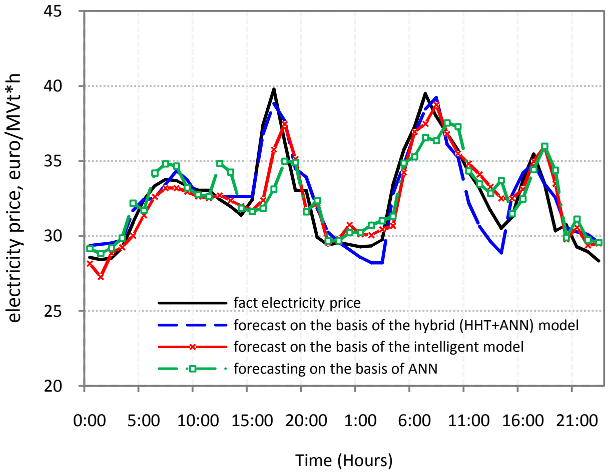

Fig. 11. Result of the hourly spot electricity prices forecasting with a lead time interval of 1 hour on the basis of different models

TABLE III. RESULT OF THE EPF ON THE BASIS OF DIFFERENT MODELS

Models	MAPE, %		Correlation coefficient, r	
	Time intervals			
	21:00 – 22:00	22:00 – 23:00	21:00 – 22:00	22:00 – 23:00
Intelligent neural model	3.09	3.64	0.83	0.90
Hybrid(HHT+ANN) model	2.30	3.37	0.96	0.92

III. Comparison of forecasts performance of the hybrid models

The proposed hybrid (HHT-ANN) model shows that the NGIS algorithm has rejected first high-frequency IMFs and first three amplitudes. This means that in EPF with a lead time interval of 1 hour the first high-frequency IMFs and first three amplitudes do not influence much the forecast of non-stationary state variables.

Here we present the comparison of forecasts performance with the hybrid (ARIMA-ANN) model proposed by Phatchakorn Areekul et al. in [29] and our HHT-ANN hybrid using the data of Australian national electricity market, New South Wales [30] for the two seasons of year 2006.

By analogy with [29] for the sake of a fair comparison, the fourth week in each of the seasons of May and October are selected. Our choice has been motivated by diverse behavior of the price on selected time intervals (see Fig. 12 and Fig. 13). It is to be noted that weeks with particularly good price behavior are purposely not sought. To build the forecasting model for each one of the considered weeks, the information available includes hourly price historical data of the four weeks previous to the first day of the week, whose prices are to be predicted.

Numerical results for EPFs with use the hybrid (HHT-ANN) model for the spring and fall are shown in Fig. 12 and Fig. 13.

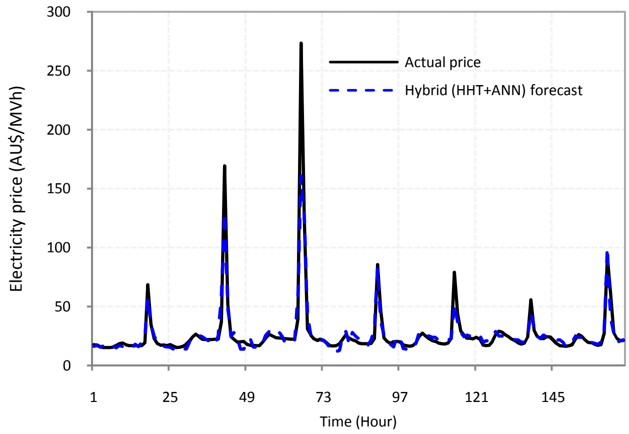

Fig. 12. Forecasting results of May 21-27, 2006 on the basis of HHT and ANN hybrid model.

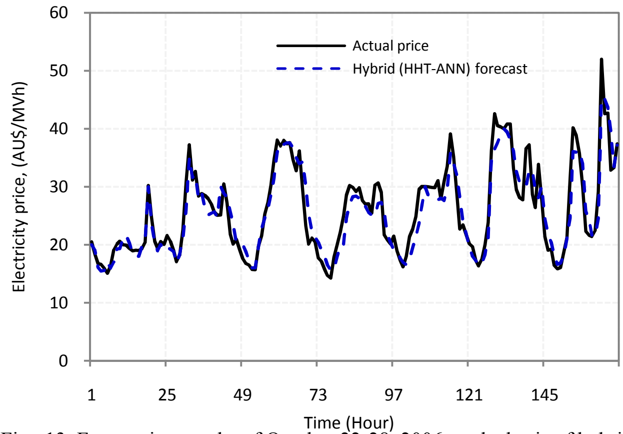

Fig. 13. Forecasting results of October 22-28, 2006 on the basis of hybrid (HHT-ANN) model

Table 4 summaries the numerical results where the comparison of EPFs of the hybrid (ARIMA-ANN) model and hybrid (HHT-ANN) model are presented. The results demonstrate that the proposed hybrid (HHT-ANN) model could provide a considerable improvement of the EPFs accuracy comparing to the hybrid (ARIMA-ANN) model. In particular, for fall and spring seasons it can be observed the reduction of all the forecasting errors. MAPE improvement comparing with hybrid (ARIMA-ANN) model range from 0.8% to 2.6% correspondingly for the fall and spring seasons, MAE improvement range from 3.25 to 0.76 correspondingly and RMSE range from 7.9 to 1.66 correspondingly.

TABLE IV. COMPARISON OF FORECASTS RESULTS FOR DIFFERENT HYBRID MODELS

Seasonal/Period	Error	Hybrid (ARIMA-ANN) Model	Hybrid (HHT-ANN) Model
Fall 21-27/05/06	MAPE (%)	13.03785	12.241267
	MAE	7.12094	3.869077
	RMSE	28.02828	20.12030
Spring 22-28/10/06	MAPE (%)	9.98647	7.41501
	MAE	2.68450	1.92452
	RMSE	4.22661	2.55719

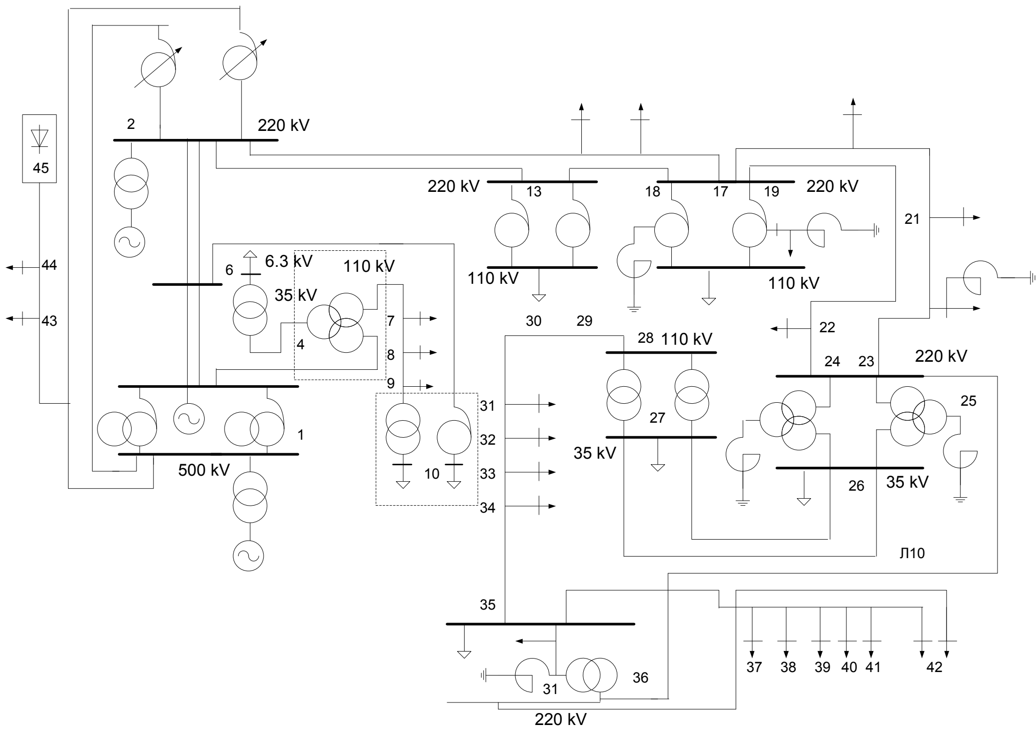

Fig. 14. Scheme of electric power system

B. *The short-term forecasting of operating conditions*

The proposed intelligent hybrid model was employed to make a short-term forecast of EPS parameters (Fig. 14):

- the active power flow in the 500 kV transmission line (TL) “1-43”;
- the frequency on the 220 kV buses at node 2;
- the voltage magnitudes at node 13.

a) Forecast of active power flow for a lead time interval of 1 minute

The developed hybrid (HHT-ANN) model has been employed to make the short-term forecasts of active power flows in the electric networks of the Interconnected power system of Siberia. The forecast was made for a lead-time interval of 1 minute.

For this purpose the studied time series was decomposed into IMFs by the EMD and the Hilbert transform was employed to obtain the amplitudes, A and the frequency, F. The latter along with the IMFs were used as input values of the selected neural network model.

Figure 15 and Table 5 summaries the numerical results where the comparison of the active power flow with anticipation 1 minute of the traditional ANN forecasting on the basis multilayer perception (MLP), specific ANN forecasting using NGIS and SA algorithms (the intelligent neural model) and the hybrid (HHT-ANN) model are presented.

The results demonstrate that the proposed hybrid (HHT-ANN) model could provide a considerable improvement of the active power flow forecast accuracy in comparison to the MLP-based ANN and the intelligent neural model.

TABLE V. COMPARISON OF THE ACTIVE POWER FLOW FORECASTS WITH ANTICIPATION 1 MINUTE FOR DIFFERENT MODELS

Period	Error	ANN type of MLP	Intelligent neural model	Hybrid (HHT-ANN) Model
20:00 – 21:00	MAPE (%)	10.1	6.7	5.2
	MAE	6.2	2.7	1.8
	RMSE	33.1	15.1	3.1
21:00 – 22:00	MAPE (%)	9.1	6.1	4.3
	MAE	6.7	2.1	1.6
	RMSE	34.1	15.1	1.7

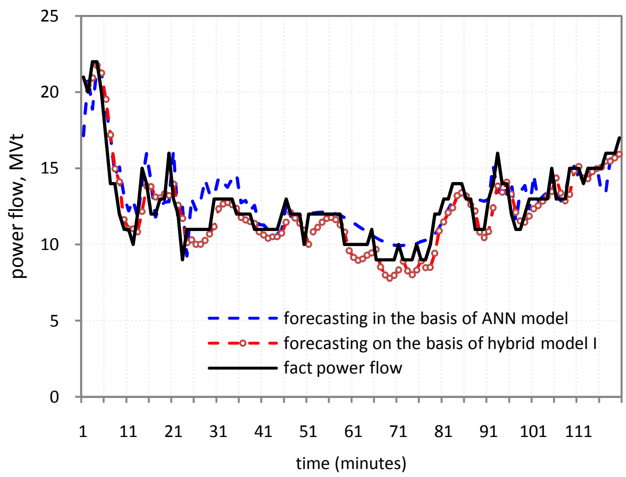

Fig. 15. Forecast of active power flow for a lead time interval of 1 minute.

In particular, decrease in the forecasting errors was observed for all considered periods. MAPE improves the forecast compared to the intelligent neural model by 1.5%

-1.8% for all periods. The improvement range for MAE is 0.9- 0.5 and that for RMSE is 12.0 - 13.4.

b) Voltage magnitude forecasting for a lead-time interval of 15 minutes

Initial time series were represented by the arrays of average 15-minute voltage magnitudes (node 13) over the period 04.02.2008 – 13.02.2008.

The voltage magnitude forecast results illustrated in Figure 16 and presented in Table 6 show that the HHT-ANN hybrid model provides good forecast accuracy.

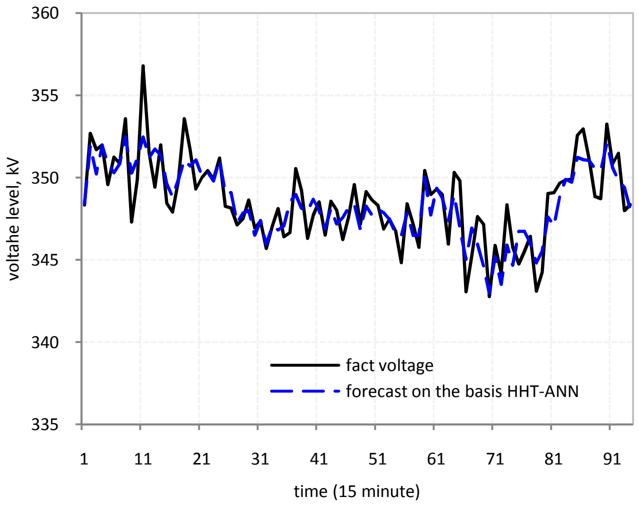

Fig. 16. Forecast of voltage magnitude (node 13) for a lead time interval of 15 minutes.

TABLE VI. THE VOLTAGE MAGNITUDE FORECAST RESULTS WITH A LEAD TIME INTERVAL OF 15 MINUTES FOR THE HYBRID (HHT-ANN) MODEL

Parameter	Mean error for an interval of 30 minutes		
	MAPE, %	MAE	RMSE
Frequency	0.29	0.99	1.29

c) Forecast of frequency on the 220 kV buses for a lead time interval of 2 minutes

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 a general regression neural network, GRNN (i.e. the 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. The results of the frequncy forecasting at node 2 are presented in Table 7 and Fig. 17.

TABLE VII. FREQUENCY FORECAST WITH A LEAD TIME INTERVAL OF 2 MINUTES FOR INTELLIGENT HYBRID MODEL.

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

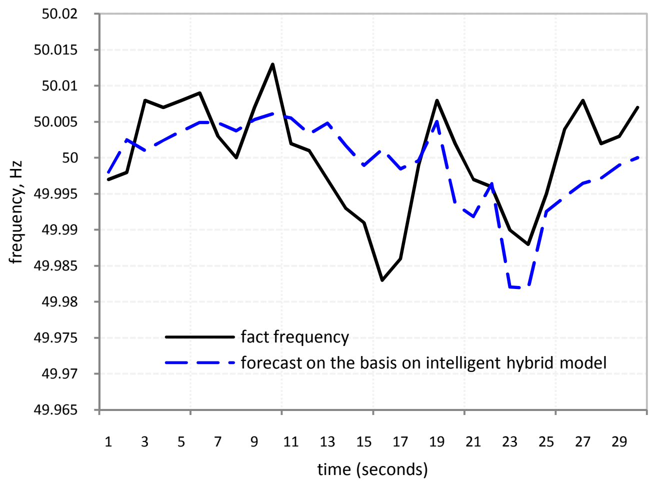

Fig. 17. Forecast of frequency at node 2 for a lead time interval of 2 minutes.

VII. CONCLUSIONS

The problem of short-term forecasting of expected operating conditions and electricity prices is studied. We propose the new two-stage adaptive approach that combines the effective technique for time series analysis Hilbert-Huang transform technology and artificial neural network forecasting technology. The proposed approach consists of two stages. 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.

The efficiency of hybrid (HHT-ANN) model is demonstrated on short-term forecast of parameters EPS and electricity prices.

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