Hybrid Genetic Algorithms for Forecasting Power Systems State Variables

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***Abstract* — A problem of forecasting state variables of electric power system is studied. The paper suggests data-driven adaptive approach based on hybrid-genetic algorithm which combines the advantages of genetic algorithm and simulated annealing algorithm. The input signal is decomposed into orthogonal basis functions using the Hilbert-Huang transform. The hybrid-genetic algorithm is applied to optimal training of the support vector machine and artificial neural network. The results of applying the developed approach for the short-term forecasts of active power flows in the electric networks are presented. The best efficiency of proposed approach is demonstrated on real retrospective data of active power flow forecast using the hybrid-genetic support vector machine algorithm empowered with the Hilbert-Huang transform.**

***Index Terms* — forecast; active power flow; genetic algorithm, support vector machine, Hilbert-Huang transform, ANN.**

I. INTRODUCTION

Complex electric power systems have a high number of process variables and a heavily interconnected and interdependent topology. The optimization of a whole system in particular, which is based on intelligent forecasting systems, could improve its performance and reduce energy consumption. Particular forecasting technologies of intelligent forecasting systems are concentrated on evolutionary computing, neural computing, fuzzy computing, probabilistic computing, data mining, etc.

The short-term forecasting of power system parameters can be carried out both with the aid of classical approaches of the dynamic estimation, statistical methods of analysis of time series and regressive models, and with the aid of technologies of the artificial intellect. It is worth noting that a change of the power systems parameters often features a sharply variable non-stationary behavior, which limits the efficiency of the stated technologies of forecasting of time series.

Many algorithms have been proposed in the last few decades for performing accurate forecasting power systems state variables. The most commonly used techniques include statistically based techniques like time series, regression techniques and Box–Jenkins models and computational intelligence method like fuzzy systems, artificial neural networks (ANNs) and neuro-fuzzy systems [1] – [6].

In forecasting the time series specified by the sharply variable non-stationary behavior, the models formed with the aid of ANNs received a rather wide extension [7], [8]. Various methods of the union of neurons together and organizations of their interaction led to the creation of ANNs of various types. Among the collection of existing ANN structures, we will point out the multiplayer perceptron, the ANN on the basis of radial-basis function, and the generalized regressive network, which found the highest application for the short-term forecasting power system state variables. An ANN learning methods provide a robust approach to approximating real-valued, discrete-valued and vector-valued target functions. The other approach to parameters forecasting is support vector machine (SVM) [8], [9].

Studies have shown that hybrid approaches, that is a combination of different intelligent techniques, have great potential and are worth pursuing [10]-[12]. One of the popular hybrid models used genetic algorithms (GA) and Hilbert-Huang Transform (HHT). GA has been increasingly applied in conjunction with other artificial intelligence techniques such as ANN and SVM.

The paper suggests data-driven adaptive approach based on hybrid-genetic algorithm which combines the advantages of genetic algorithm and simulated annealing algorithm [13], [14].

II. BACKGROUND

In 2010 the concept of Intelligent Energy System with Active and Adaptive Network (IES AAN) [15] has been employed in order to develop and operate the main electric networks in Russian Federation [16], [17]. The IES AAN technological infrastructure is shown in figure 1. One of the most important problems in this area of focus is the organization intelligent monitoring conditions and their control with the use of novel forecasting methods, especially methods of artificial intelligence. Development of the state of the art techniques for robust forecasting of behavior of nonlinear and non-stationary power systems is one of the challenges for electrical power systems (EPS) development.

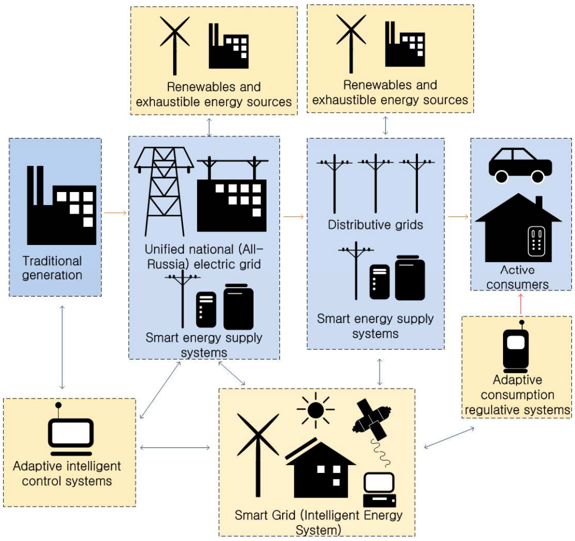

Figure 1. The IES AAN technological infrastructure.

Advanced smart devices and technologies, such as PMU, artificial intelligence and so on give new possibilities for solving complex and comprehensive problem of emergency control using monitoring, forecasting and control of EPS operating conditions. Time sequence of individual stages of monitoring, forecasting and control of operating conditions is shown in Fig. 2 [18].

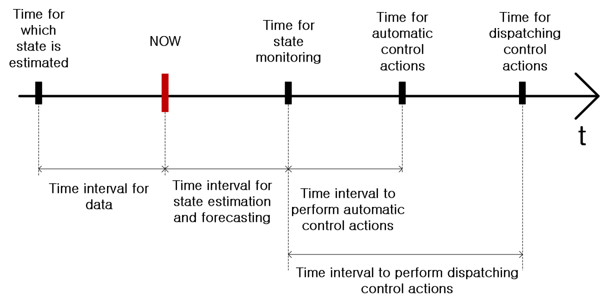

Figure 2. Time diagram of events in the system for monitoring, forecasting and control in EPS.

The present issue intelligent forecasting systems in the IES AAN will focus on accurate energy demand modelling intelligent computation approaches to provide well energy planning and accurate energy expenditure prediction. The IES AAN operating normal and emergency conditions must be controlled in an intelligent way, based on forecasts and coordinated with operation of other units in the power system [19]. Such a control, based on forecasts, implies intelligence. Particular forecasting technologies of this issue are concentrated on evolutionary computing, neural computing, fuzzy computing, probabilistic computing, wavelet transform, etc.

Forecasting is a vital part of business planning in today competitive environment. With increased penetration of renewable energy sources and introduction of deregulation in power industry, many challenges have been encountered by the participants of the electricity market. Forecasting of wind power, electric loads, power flows, frequency, energy price and etc. have become a major issue in power systems. But it's important to note that each of these parameters can exhibits its own stylized features and is therefore forecasted in a very different manner.

An introduction of competitive mechanisms a power system states planning and control, an expansion of power system states control coordination causes rapid dynamics of an electric power system conditions. The development of an accurate, fast and robust short-term forecasting power system state variables methodology is of importance to both the electric utility and its customers.

III. NOVEL GENETIC HYBRID APPROACH FOR FORECASTING POWER SYSTEMS STATE VARIABLES

A. *HHT algorithm*

For more accurate forecasting of power state variables we use a preprocessing of initial data by the Hilbert-Huang Transform (HHT). HHT is the two-steps algorithm, combining the empirical mode decomposition (EMD) and the Hilbert spectral analysis (HSA). In general, this algorithm can be presented in the chart (Fig. 3). For more information, relating to EMD process and Hilbert spectrum analysis, see [20] - [22].

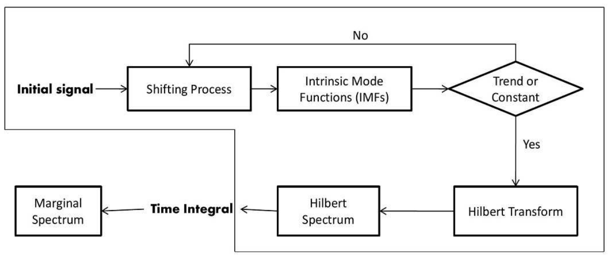

Figure 3. The flow chart HHT configuration.

After the HHT was employed we obtain, through EMD and HT, the sets of IMFs, instantaneous amplitudes and frequencies. These sets are used as input values of the selected ANN or SVM models.

B. *Hybrid genetic algorithm*

Figure 1 shows general forecasting scheme. There are three main blocks. First two blocks preprocess input data with

HHT and hybrid genetic algorithm enables the optimal features selection and formation of the optimal ANN architecture. The same blocks are employed for the parameters selection of the support vector machine regression.

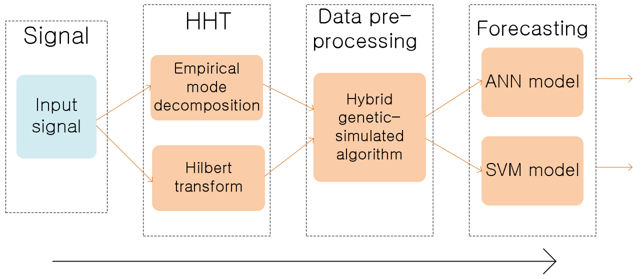

Figure 4. Block diagram of the proposed hybrid genetic approach scheme.

Let us describe the hybrid genetic algorithm more in details. The hybrid genetic algorithm (HGA) [14] consists of two algorithms. It combines the advantages of simulated annealing (SA) and GA [13].

GA can be applied in many areas, it can handle any form of objective function and constraints, whether it is linear or non-linear, continuous or discrete, and theoretically lead to the optimal solution. However, in practical application GA faces serious problems, namely: premature convergence, poor local optimization capability, and slow convergence and no convergence to global optimal solution. In recent years, many authors have worked to improve the GAs, in particular through encoding scheme modifications, selection of fitness function and genetic operator design.

The SA is a generic probabilistic algorithm for the global optimization problem, namely locating a good approximation to the global optimum of a given function in a large search space. This algorithm is able to avoid becoming trapped at local minima.

C. *Hybrid (GA-ANN) algorithm*

One of the major problems in ANN training is the formation of an optimal input sample. An effective way of solving this problem is to use nonlinear optimization algorithms, namely SA method and neuro-genetic selection of input data (NGIS), which provides a procedure for selecting the best predictive model for each sample. In the training data analysis the NGIS algorithm retrieves the input data which can be discarded as less informative. This method employs optimization procedure based on random search methods, and combines the capabilities of genetic algorithms and ANNs, namely Probabilistic and General Regression Neural Networks (PNN/GRNN) in order to automatically find optimal combinations of input variables. Such optimized GRNN-networks can be considered as models with memory because they "remember" the best results, causing the final results improvement. The radial basis functions in PNN helps to provide robustness of "bad data" in the input sample.

The SA technique makes it possible to analyze properties of the initial sample and to organize a “competition” system between various ANN-based forecast models, when the best neural model of forecasting is chosen in the process of nonlinear optimization.

D. *Hybrid (GA-SVM) algrithm*

GA is used to optimize both the feature subset and parameters of SVM simultaneously for power state variables forecasting. In general, the choice of the feature subset has an influence on the appropriate kernel parameters and vice versa. Therefore the feature subset and parameters of SVM need to be optimized simultaneously for the best prediction performance.

The procedure starts with the randomly selected chromosomes which represent the feature subset and values of parameters of SVM. Each new chromosome is evaluated by sending it to the SVM model. The SVM model uses the feature subset an values of parameters in order to obtain the performance measure (e.g. hit ratio). This performance measure is used as the fitness function and is evolved by GA.

IV. CASE STUDY

The novel genetic hybrid approach is realized in STATISTICA 8.0. and Matlab. In this paper, we demonstrate the proposed approach on the Western Baikal-Amur Mainline (BAM) power supply system. The real power supply system shown in Fig. 5. The BAM external power supply is carried out the 110 kV power network (from “Taishet’’ to “Lena” substations) and the 220 kV power network (from “ Lena” to “Taksimo” substations).

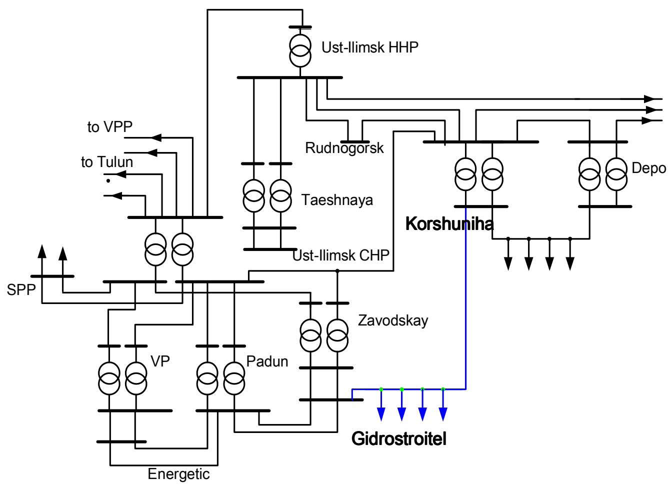

Figure 5. Western BAM power supply system.

The presence of a draft load in the BAM power supply system causes in the sub-transmission network an appearance of asymmetry above an allowable value. Traction substations are conventional transformer substations and located at a distance of 25-50 km, an overhead system size and a conductor losses are much less than in a DC system. It is known that an alternating-current draft load is a single-phase, so substation loads supplying an alternating current locomotive, are always a priori asymmetric, with sharply varying in time asymmetry. Continuous and random changes in time traction load, a presence of a two-way feed greatly complicates a forecasting state variables.

Forecasting active power flows provides an estimation of transmission capacity reserves in expected operating conditions in order to preserve of weak tie-line stability for an internal and external sections of an EPS by issuing appropriate control actions on a control stations and power units.

The initial train data is represented the telemetric data of the per-minute active power flow for 3 days (4320 values). For this purpose the studied time series was decomposed into IMFs by the Huang method (Fig. 6), and the Hilbert transform was employed to obtain the amplitudes, *A*. The latter along with IMFs were used as input values of the selected HHT-ANN and HHT-SVM models.

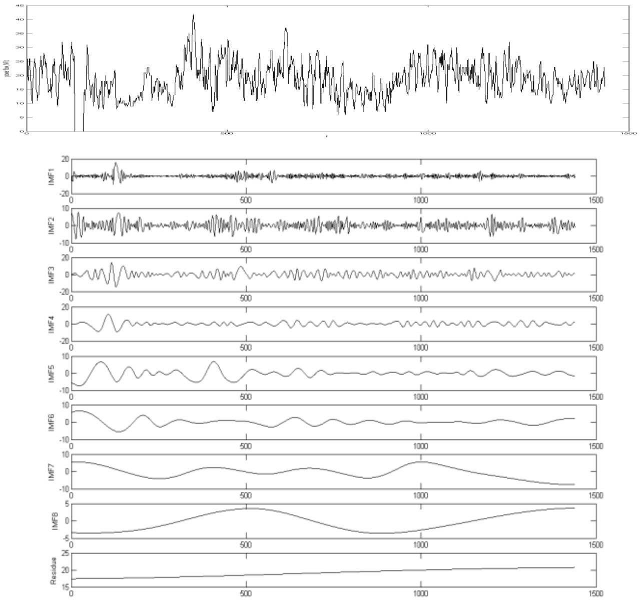

Figure 6. The real active power flow in 04.02.11 (top). Results of EMD applied (bottom).

The constants of a GA have been chosen as population size 100 and generation size 20. It had been also chosen the following genetic operators: crossover rate 5, mutation rate 0.1. Employment the optimization unit HGA for an ANN selection has demonstrated the advantage of MLP architecture (Table I). It's important to note that in case of the final MLP model were excluded the following components as insignificant values: IMF1, A4, A6, A7, F1, F2, F3, F6.

The MLP model summary is presented in Fig. 7 and Table II. The code BFGS 27 in Table 3 indicates that the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm [23] was used and that the MLP network was found on the 20th cycle on the basis hybrid genetic algorithm. A BFGS (or Quasi-Newton) is a powerful second order training algorithm with very fast convergence but high memory requirements due to storing the Hessian matrix.

TABLE I. EMPLOYMENT THE OPTIMIZATION UNIT HGA FOR AN ANN SELECTION

Iteration	ANN model	Test error MAE, MWt	Input neurons	Hidden neurons	Performance
16	RBF	0.071	14	109	0.43
17	RBF	0.069	14	112	0.41
18	RBF	0.072	14	116	0.42
19	RBF	0.070	14	111	0.41
20	MLP	0.087	21	8	0.38
21	GRNN	0.082	25	25-2158	0.24
22	GRNN	0.083	25	25-2158	0.21
23	MLP	0.062	16	6	0.41
24	MLP	0.059	17	4	0.39
25	**MLP**	**0.056**	**16**	**5**	**0.38**

TABLE II. ANN MODEL SUMMARY.

Type and structure of ANN	MLP 8-5-1
Training performance	0.9439
Test performance	0.9470
Training error	0.001395
Test error	0.001320
Training algorithm	BFGS 20

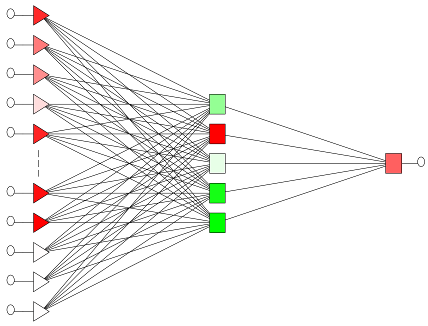

Figure 7. The MLP network structure for a "1 minute ahead" active power flow forecasting.

The HGA result for the SVM model is shown that were excluded the following input components as insignificant values: A1, A5, A8, F1, F2, F3, F4, F6, F7. The SVM model parameters were determined empirically - enumerative technique. It should be noted that, in this case, a SVM significant characteristic, which is influenced at a forecasting accuracy were a kernel parameter γ – specifies the gamma parameter for RBF (Table III).

TABLE III. SVM MODEL SUMMARY.

Number of independents	8
SVM type	Regression type 1 (capacity = 10, epsilon = 0.4)
Kernel type	RBF (γ=0.001)
Number of SVs	1546

To compare a forecasting approaches performance, the authors also had calculated similar a "1 minute ahead" active power flow forecasts on the basis of conventional approaches: Autoregressive integrated moving average (ARIMA), ANN and Multiplicative Exponential Smoothing.

Table IV and Fig. 8 summaries the numerical results for a "1 minute ahead" active power flow forecasting on based on the HHT-GA-ANN and HHT-GA-SVM models. The active power flow forecast results show that the hybrid HHT-SVM model provides best forecast accuracy.

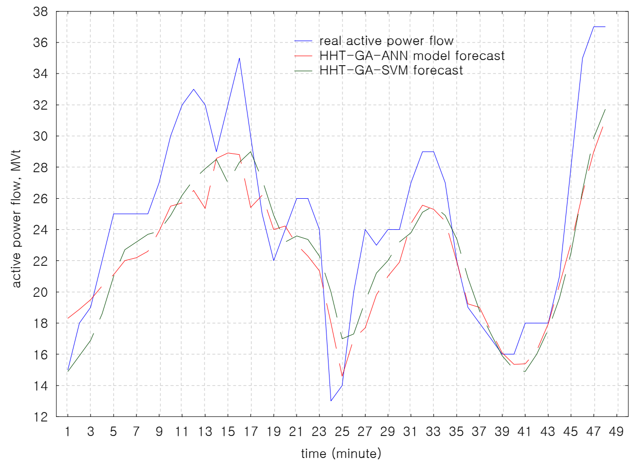

Figure 8. Result of a "1 minute ahead" active power flow forecasting on based on hybrid genetic models.

TABLE IV. COMPARISON OF A "1 MINUTE AHEAD" ACIVE POWER FLOW FORECASTS ON THE BASIS A HYBRID AND CONVENTIONAL APPROACHES.

№	**Forecasting models**	**Error**		
		MAPE, %	*MAE, MVt*	*RMSE, MVt²*
1	HHT-GA-ANN	12,5	3.2	3,9
2	HHT-GA-SVM	11,6	2.9	3,5
3	ANN	15,8	6,9	33,6
4	ARIMA	22.4	7.1	7.4
5	Multiplicative Exponential Smoothing	34.2	10.8	10.9

As Table IV is shown the most accurate forecast was gave the hybrid HHT-GA-SVM and HHT-GA-ANN models (MAPE - 11.6% and 12.5% respectively), compared with the conventional approaches: the ANN model – 15,8, the ARIMA model – 22.4 % and the Exponential Smoothing – 32.2%. Besides the HHT-GA-SVM gives smaller errors compared to the HHT-GA-ANN.

Abbreviations, such as MAPE, MAE, RMSE, in table I and table IV are calculated as follows

MAPE metric:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|x_t - \overline{x}_t\right|}{x_t}\cdot 100\%\,; \qquad (1)$$

mean absolute error (MAE metric):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|x_t - \overline{x}_t\right|; \qquad (2)$$

root mean squared error (RMSE metric):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \overline{x}_t)^2}\,, \qquad (3)$$

where $x(t)$ is actual value of parameter at moment t, $\overline{x}(t)$ is forecasted value of parameter at moment t and n is the number of measurements.

V. CONCLUSIONS

In this paper we studied the problem of forecasting of power state variables. The main contribution is the data-driven adaptive approach based on the hybrid-genetic algorithm which combines the advantages of the genetic algorithm and the simulated annealing algorithm.

Our approach combines an efficient method for non-stationary time series analysis based on the empirical mode decomposition and the Hilbert integral transform. We employed the machine learning technologies such as artificial neural networks and support vector machine trained with nonlinear optimization algorithms, namely simulated annealing and genetic algorithm.

The efficiency of proposed methodology is demonstrated on short-term forecasts of active power flows in the Western Baikal-Amur Mainline power supply system in Siberia.

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REFERENCES

[1] G.E.P. Box and G. Jenkins, Time Series Analysis, Forecasting and Control. San Francisco, CA: Holden-Day, 1970 – 316 p.

[2] G. Zhang, E.B. Patuwo, and M.Y Hu, "Forecasting with artificial neural networks: The state of the art," *J. Forecasting,* vol. 14, 1998, Pp. 35-62.

[3] S. Makridakis. A. Anderson, R. Carbone, R. Fildes, M. Hibdon, R. Lewandowski. J. Newton. E. Parzen. and R. Winkler, "The accuracy of extrapolation time series methods: Results of a forecasting competition," J. Forecasting, vol. 1, 1982, pp. 111-153.

[4] N. Kohzadi, M. S. Boyd. B. Kermanshahi. and I. Kaasrra, "A comparison of artificial neural network and time series models for forecasting commodity prices." Neurocomputing, vol. 10, 1996, pp. 169-181.

[5] Osowski S. Neural Networks for Information Processing. OWPW: Warzsava, 1996.
[6] Lambert-Torres, G. "Fuzzy techniques for load forecasting." IEEE Power Engineering Society Summer Meeting, vol. l, 2000, pp.178-179.
[7] Gamm, A.Z., Glazunova, A.M., Grishin, Yu. A., Kurbatsky, V.G., Sidorov, D.A, Spiryaev, V., Tomin, N.V. “Forecasting power system state variables methods for a monitoring and control,” Theoretical and Scientific Journal “Electrichestvo”, Vol.5, 2011. 12-20 (In Russian).
[8] V. Vapnik, C. Cortes. Support-Vector Networks, Machine Learning, 20, 1995.
[9] K.-R. Muller, A.J. Smola, et al. Predicting Time Series with Support Vector Machines. In Proceedings of the 7th International Conference on Artificial Neural Networks (ICANN '97), Wulfram Gerstner, Alain Germond, Martin Hasler, and Jean-Daniel Nicoud (Eds.). Springer-Verlag, London, UK, 2007 p. 999-1004.
[10] Kurbatsky V., Sidorov D., Spiryaev V., Tomin N. On the Neural Network Approach for Forecasting of Nonstationary Time Series on the Basis of the Hilbert–Huang Transform. Automation and Remote Control, 2011, Vol. 72, No. 7, 2011, 1405–1414.
[11] Zhigang Liu, Weili Bai and Gang Chen. "'A new short-term load forecasting model of power system based on HHT and ANN", Proc
[12] G. P. Zhang. "Time series forecasting using a hybrid AR1MA and neural network model," Neurocomputing, vol. 50, 2003, Pp. 159-175.
[13] S. Haykin. Neural networks. A comprehensive foundation. Second edition - Williams Publishing House, 2006. - 1104 p.
[14] Shi, Huawang, Li, Wanqing. Evoving Artificial Neural Networks Using Simulated Anneling-based Hybrid Genetic Algorithms. Journal of Software, 5(4), 2010.
[15] FGC UES, “The concept of development of a smart electric power system of Russia with an active-adaptive network”, M. 2011, (in Russian).
[16] N.I. Voropai. Smart Grid: myths, reality, perspectives, *Energeticheskay politika*, vol. 2, pp. 9-13, 2010.(in Russain).
[17] V.V. Dorofeev, A.A. Makarov. *Active-adaptive power network – new quality of UES of Russia*, Energoexpert, vol. 4, 2009.
[18] 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” in Proc. Conference on Control Methodologies and Technology for Energy Efficiency (CMTEE-2010), Vilamoura, Portugal, 2010.
[19] Voropai, N., Kurbatsky, V., Panasetsky, D., Tomin, N. and other., “Coordinated Intelligent Operation and Emergency Control of Electric Power Systems”, Chapter 1. Innovation in Power, Control, and Optimization: Emerging Energy Technologies. IGI Clobal, 2011. Pp. 1 - 56.
[20] H.E. Huang, Z. Shen S.R. Long, M.C. Wu, H.H. Sliih, Q. Zheng, N.C. Yen, C.C. Tung, H.H. Liu. “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis”. Proc. R. Soc. Lond. A (1998) 454. Pp. 903-995.
[21] G. Rilling, P. Flandrin, P. Goncalves. “On Empirical Mode Decomposition and its Algorithms”, IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing NSIP-03, Grado (I), 2003.
[22] Hui Li, Yuping Zhang and Haiqi Zheng, Hilbert-Huang transform and marginal spectrum for detection and diagnosis of localized defects in roller bearings. Journal of Mechanical Science and Technology (KSME Int.J.), 20(11)(2006) 1781-1789.
[23] C. Zhu, R.H. Byrd, P. Lu, J. Nocedal. Algorithm 778: L-BFGS-B, Fortran subroutines for large scale bound constrained optimization, ACM Transactions on Mathematical Software, Vol. 23, Issue 4, 1997, pp. 550-560.