APPLICATION OF MACHINE LEARNING ALGORITHMS IN THE PROBLEMS OF IMPROVING MODE RELIABILITY OF MODERN POWER SYSTEMS

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Abstract

In order to increase the regime reliability of energy systems, the experience of applying machine learning algorithms and models for various issues of operative-dispatching and counter-accident management was reviewed. It is indicated that an effective solution to this problem is the use of machine learning algorithms and models that are able to learn to predict and control the operating modes of the power system, taking into account many changing influencing factors. The experience of using machine learning technology in the tasks of operational dispatch and emergency control of EPS is presented, which clearly shows the prospects of such studies for subsequent practical implementation in the work of various automated control systems for electric power networks of power systems. Until recently, models based on neural network structures have remained the most popular among machine approaches in predictive problems. The advantages of using this structure are shown, first of all, by the fact that the neural network structure makes it possible to obtain models with good approximating abilities. A comparative analysis of the effectiveness of various models in predicting electricity consumption is given. The issues of voltage and reactive power regulation in the electrical network of power systems using an artificial neural network are considered and the effectiveness of this approach is shown. A model and algorithm for estimating voltage stability in power system nodes under various influencing factors is proposed, as well as results are presented that confirm the reliability of the results obtained.

Keywords: power system, electric power system, artificial intelligence, machine learning, operational control of power system modes, mode prediction, artificial neural network, voltage and reactive power regulation

1. Introduction

A characteristic feature of the trend in the development of modern energy systems is the

increase in the share of non-traditional energy sources - these are alternative energy sources, such as wind turbines, solar PV installations, geothermal, converters, fuel cells and other types of renewable sources. The generation of power from non-traditional sources such as wind and solar power plants is stochastically variable, and for this reason the system operator cannot control their generation.

The development of artificial intelligence (AI) methods made it possible to significantly speed up and automate the solution of this and a whole range of tasks for managing the modes of electric power systems (EPS) in the context of integrating renewable energy sources (RES) [1]. In recent decades, one of the actively developed areas within the Smart Grid technology platform is the use and implementation of machine learning (ML) technology, which includes methods for constructing algorithms that can learn. The use of various types of learning ML models: with a teacher (Supervisedlearning), without a teacher (Unsupervisedlearning), with reinforcement (Reinforcementlearning), deep learning (Deeplearning), etc., made it possible to create original adaptive, trainable software modules regulation and control of both individual devices and subsystems of the EPS, and its mode as a whole. Their main advantages are speed, high adaptability, the ability to approximate nonlinear functions and the presence of a certain kind of machine intelligence, which allows developing the most autonomous systems capable of independent decision-making based on experience and original generalization properties.

The article reflects the experience of using the authors of algorithms and models of ML for various tasks of operational dispatch and emergency control of EPS, concomitant with an increase in the regime reliability of power systems.

II. Review of the application of ml in problems of operational control of power system modes

A necessary condition for the effective management of modern EPS is the availability of a short-term forecasting tool. The relevance of this task is predetermined by the fact that when analyzing and forming control actions only according to past data, a delayed reaction to the behavior of the EPS is obtained, which causes overestimated requirements for static and dynamic stability reserves, and also reduces the efficiency of control systems.

Traditionally, the task of short-term forecasting of parameters in the EPS was carried out mainly using statistical methods based, for example, on the autoregression of the integrated moving average (ARMA), the Kalman filter [2]. An analysis of modern scientific works indicates that for the problem of short-term forecasting of EPS parameters, ML methods, primarily artificial neural networks (ANN) [5-7], support vector machine (SVM) [5], decision trees (DT) are widely used [6].

Until recently, ANN-based models remained the most popular among machine approaches in predictive problems. The success of ANN application is due, first of all, to the fact that the neural network structure makes it possible to obtain models with good approximating abilities. Various ways of combining neurons with each other and organizing their interaction led to the creation of different types of ANNs, among which the most widely used for short-term forecasting of EES parameters was found: a multilayer perceptron (MP), an ANN based on radial basis functions, an Elman network and a generalized regression network.

Along with ANNs, predictive models based on SW demonstrate high efficiency [7]. Methodologically, SVM, like ANN, is based on the well-known Cover theorem [8] on increasing the probability of linear separability of images when transforming a nonlinear problem of classifying images into a space of higher dimension. In [9], a comparative analysis of the effectiveness of various models in predicting electricity consumption in one of the energy Hong

Kong. The measurements were carried out daily throughout the year. After processing the data, three models for predicting energy consumption were built: linear regression, ANN, DT. As can be seen from Table 1, the best results are given by the DT and ANN models with a deviation from the

true value of 5-6%.

Table 1: *Electricity consumption forecast results in one of the power districts of Hong Kong based on various models of ML*

Forecasting model	Average relative error, %
Linear regression	7.6-8.2
Artificial neural network	5.5-6.7
Decision Trees	4.8-5.6

DT|-based models are a promising technology for predicting complex non-stationary implementations that cannot always be processed based on neural network models. The structure of DT is "leaves" and "branches". The edges (“branches”) of the decision tree contain the attributes on which the objective function depends, the “leaves” contain the values of the objective function, and the remaining nodes contain the attributes by which the cases are distinguished. The DT model makes it possible to obtain stable solutions comparable to SVM and ANN without using the large computing power required by previous models.

At the same time, the most popular modification of the AR algorithm used for forecasting problems is the "random forest" (from the English RandomForest) models, which allow you to build many trees on different subsets of the training sample and, due to the law of large numbers, get the best results by choosing the average of all prediction trees. In [10], a large-scale study of DT committee (ensemble) models is presented - random forest and gradient boosting for intra-day wind speed forecasts for wind power stations (WPPs) of Sotavento (Spain) and wind generation throughout Spain. The performance of DT-based models was compared with MOW and MT as the most popular MT models for wind generation forecasting. However, the results obtained did not reveal a clear “winner” (Table 2).

At the forecast level for a single WPP, the models based on the DR committee outperform the MOU model. At the same time, forecasts for the entire EPS of Spain showed that the results of the DT are close to the accuracy indicators of the SRM. And finally, the lowest forecast accuracy for these cases was recorded when using MP models.

Table 2: *Forecast errors, MAE for WPP Sotavento and EPS of Spain*

Models	WPP "Sotavento"		Wind power for Spain's EPS	
	Training	Test	Training	Test
Support Vector Machine	5.62	7.80	1.01	3.13
Random forest	2.68	7.68	1.29	3.68
Gradient boosting	3.69	7.84	1.06	3.41
Extreme gradient boosting	2.43	7.72	0.90	3.22
Multilayer perceptron	5.61	7.78	1.22	3.69

The development and application of ML methods made it possible to significantly speed up and automate the solution of a whole range of tasks of regime and emergency control of EPS. At the same time, most of the solutions in this direction are associated with the transformation of the classical optimization problem into a regression/classification problem, which can significantly reduce the calculation time while maintaining acceptable accuracy. The most successful developments have been obtained in the field of application of various DT algorithms for monitoring and controlling the operational reliability of EPS: online DT models for voltage/reactive power regulation [11], random forest models for monitoring the dynamic operational reliability of EPS (separate developments of the Hydro-Québec energy companies), Canada [12] and

Energinet.dk, Denmark [13]).

Significant progress in the control of EPS modes was obtained on the basis of a group of ML methods with reinforcement, such as Monte Carlo methods, dynamic programming, learning based on time differences (SARSA, Q-learning), etc. [14]. These methods involve learning what to do, how to map situations into actions in order to maximize some reward (reward) signal that takes numerical values. The model being trained (the agent) is not told what action to take, as is the case in most ML approaches. Instead, they must try different actions and find out for themselves which ones will bring him the greatest reward.

As a result, this approach allows the agent to choose an EPS control strategy not randomly, but to take into account the experience of previous interaction with the system based on the assessment of the utility function Q. Agents trained offline based on the Q-algorithm successfully control individual components of the power system within the ODE and / or PAHs such as dynamic brake, thyristor-controlled series capacitor, synchronous generators, individual or aggregated loads, etc. for optimal control strategies. Applications of the reinforcement learning method have shown good results in a whole range of ODE and PAC tasks: wind turbine generation control, load control, power system restoration, micro-EPS modes control, voltage regulation, cascade accident prevention, power consumption forecasting, etc. [15,16].

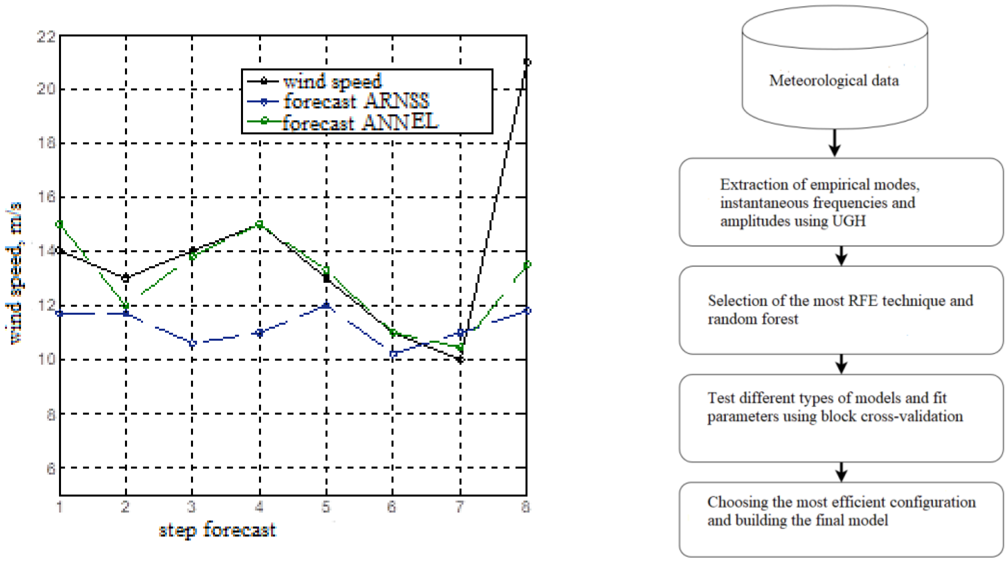
Despite the undoubted advantages of the noted ML models, the question of the high efficiency of these methods is still open and requires further research. One of the most promising areas is the use of hybrid approaches. In [17], ANN and SW models are considered in combination with the Hilbert-Huang transform (HCT). In [18], the Box-Jenkins methodology was supplemented with ANN. Neural network models together with fuzzy logic methods were proposed in [19]. Models combining ANN and burst theory are presented in [20]. The success of hybrid approaches is explained by dividing the task of constructing a predictive model into two basic stages: the stage of data preprocessing in order to identify features that are most significant for the prediction, and the stage of identifying a dynamic predictive model itself.

III. Short-term forecasting of power system parameters using ml models

The scientific groups of ISEM SB RAS (Irkutsk, Russia), "Azerenergy" and AzNIiPIIE (Baku, Azerbaijan) conducted a study of autoregression models and neural networks in predicting the power generation of offshore wind turbines in various sectors of the Caspian Sea [21]. To build and train models, we used data from measurements of wind speeds and a number of other additional parameters (Fig. 1a). To predict the power of wind turbines in intraday cycles "for 1 hour ahead"', the prehistory of data for one week was used. (averaging 5 minutes). According to the test results, the Artificial Neural Network for Extreme Learning (ANN EL) gave a significantly higher prediction accuracy (MAE = 2.538, RMSE = 2.686) than the autoregressive ARNSS model (MAE = 6.649, RMSE = 7.178).

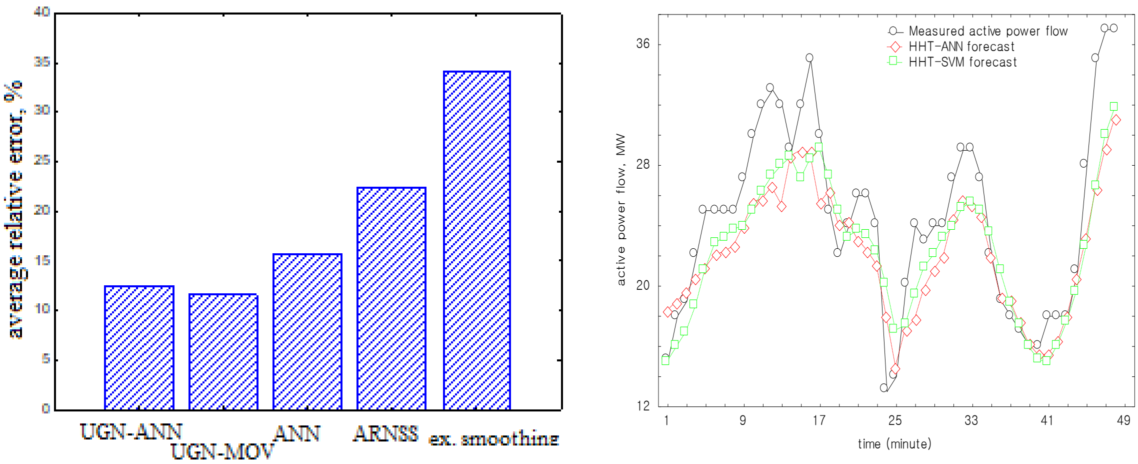
The staff of ISEM SB RAS, together with the research team of the Irish National University in Cork, developed a hybrid approach (Fig. 1b) to short-term forecasting of EPS parameters (load, generation, power flows, electricity prices) based on an effective apparatus for analyzing non-stationary time series UGH and ML algorithms [17,22].

UGH can be divided into two parts: empirical mode decomposition (SEM) and the application of the Hilbert transform to them. This makes it possible to obtain a set of frequencies and amplitudes localized in time. There are various SEM-based hybrid approaches that include modifications of ML algorithms for dependency recovery. Various types of ANN (MP, ANN EL), MOV and others are used as such algorithms.



a) б)

Figure 1: *Results of wind speed forecast based on the ARPSS and ANN EL models (a) and the general diagram of the hybrid approach for creating forecast models (b)*



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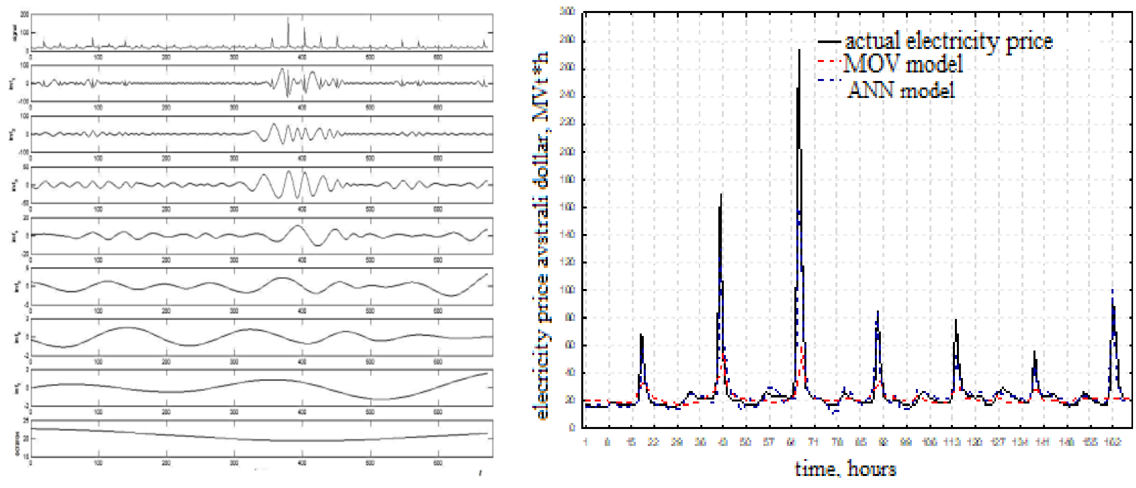
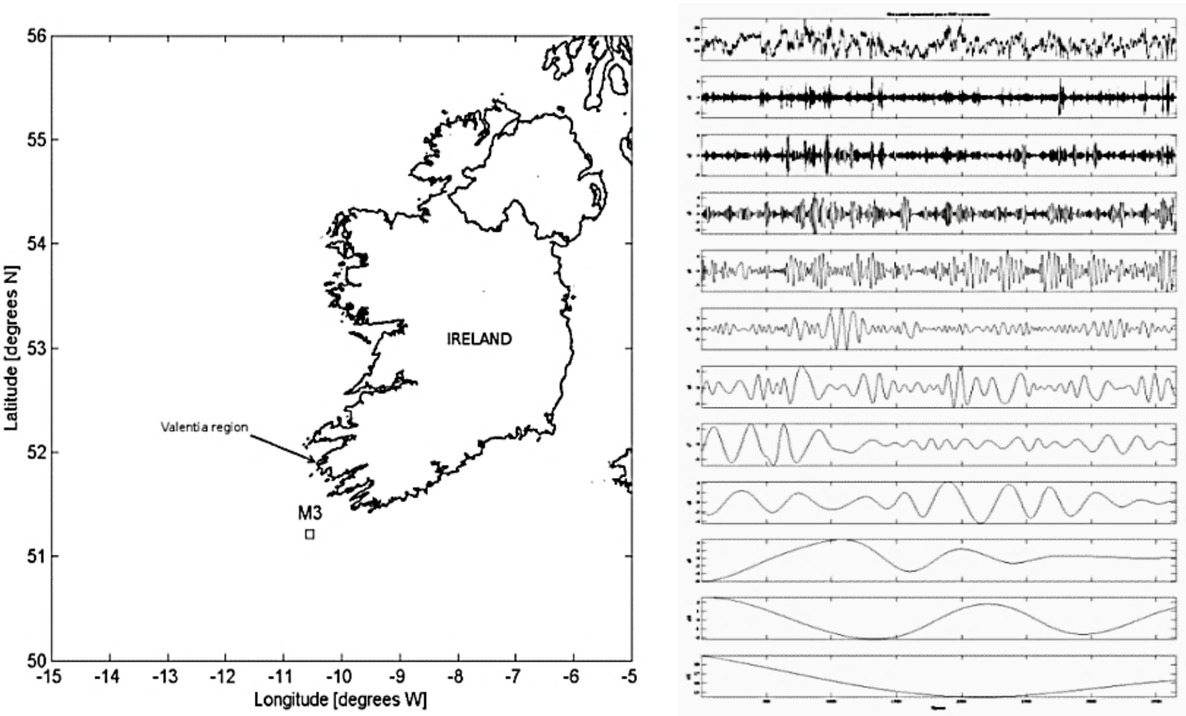


c) d)

Figure 2: *Application of the hybrid approach: a, b - the results of forecasting the flow of active power "for 1 hour ahead"; c - the results of the SEM of electricity prices for the South Wales area; d - forecast schedule for electricity prices in the Australian market "1 hour ahead"*

The effectiveness of this hybrid approach has been demonstrated on real data in various test tasks: in ultra-short-term forecasting of active power flows in the section of the traction substation "Gidrostroitel-Korshunikha", Russia, Irkutsk region (Fig. 2, a, b) [23] and in forecasting electricity prices “1 hour ahead” according to the Australian National Energy Exchange (Fig. 2, c, d) [17].

Additionally, the hybrid approach was tested on real data when predicting wind speed “for 24 hours ahead” for the tasks of controlling the modes of wind power plants in the region of Valentia, Ireland (Fig. 3) [22]. In addition to retrospective data on wind speed and direction, such characteristics as atmospheric pressure, wave height and period, maximum gust speed, relative humidity, and water temperature were used. All parameters were measured hourly from 12/15/2020 to 05/15/2022.

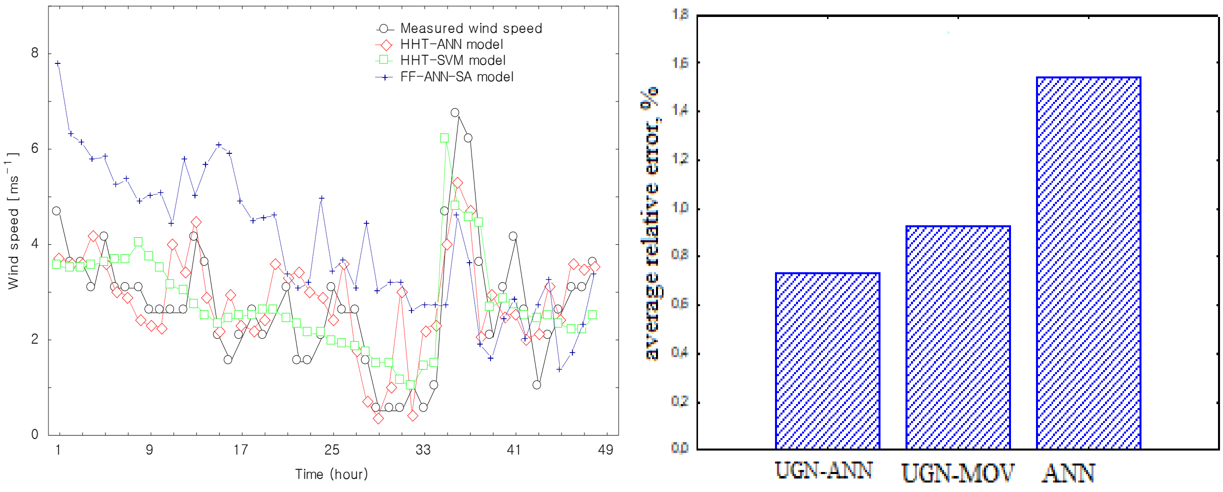


a) b)

Figure 3: *Location of the M3 weather station in the Valentia region (a) and a fragment of the decomposition of the implementation of the wind speed into empirical modes (b)*

Models were built to make forecasts 4, 6 and 24 hours ahead. The results of model testing were compared for various methods, such as random forest, SVM, DT based on gradient boosting, ANN EL. As can be seen from fig. 6, the use of the hybrid approach makes it possible to improve the accuracy of the wind generation forecast compared to the use of simple neural network forecasting.

Studies have shown that for short-term and ultra-short-term forecasts of wind generation, the most suitable of the considered methods are ANN EL and gradient boosting tree. Forecasting for a longer period requires the use of more complex and robust methods such as gradient boosting tree and random forest.



a) b)

Figure 4: *Forecasting wind speed "for 24 hours ahead"(a), Valentia, Ireland for hybrid models UGH-ANN, UGH-MOV and MP (b)*

Table 3: *Comparison of errors of various ML models*

Model	Period, hour	RMSE	MAE
Naive forecast		1.834	1.392
ANN EL		1.359	1.076
gradient boosting	4	1.416	1.112
MoU		1.848	1.463
random forest		1.429	1.127
Naive forecast		2.208	1.708
ANN EL		1.669	1.322
gradient boosting	6	1.676	1.312
MoU		2.597	2.206
random forest		1.677	1.344
Naive forecast		2.757	2.081
ANN EL		2.259	1.844
gradient boosting	24	2.157	1.708
MoU		3.480	2.620
random forest		2.235	1.835

Detailed information about the quality of models obtained by different ML algorithms for different prediction periods is presented in Table 3. As a result, for ultra-short-term (up to 4 hours ahead) and short-term forecasts for wind energy (up to 6 hours ahead), the most suitable of the considered methods are ANNs of extreme learning and gradient boosting tree. Forecasting for a longer period (up to 24 hours ahead) requires the use of more complex and robust methods such as gradient boosting tree and random forest.

IV. Voltage and reactive power regulation in Eps with integrated res using ml models

On fig. Figure 5 shows the schedule of daily power generation on one of the typical days during the month [24-26]. As can be seen from this figure, the power generation by wind farms differs significantly by day - the difference is for calm and windy days (0 - 5) % and (70 - 90) %, respectively. Differences can also be significant in power generation in the morning and afternoon. The variability of production can be so significant that the difference from the average monthly day or the average annual day is not consistent with stochasticity. The output varies throughout the day from zero to maximum. In this case, the modeling of the development characteristic in the form of a normal distribution seems to be unsuccessful, and therefore the consideration of the development process as stochastic is incorrect. In similar situations, controlling voltage and reactive power and ensuring reliability, as well as voltage stability of the EPS by traditional means, turns out to be difficult and inefficient. Therefore, the problem of applying ML to solve this problem is considered.

In [27-29], a method for estimating the EPS stability limit by the variability of the voltage profile described by the ANN (Fig. 6), developed by the scientific groups of "Azerenergy" and AzSRDSIE (Baku, Azerbaijan), is given.

In this case, the place and volume of the additionally included reactive power injection is determined by analyzing the sensitivity of the voltage stability limit value relative to the voltage variability in each network node:

$$\frac{\partial \Pi_U}{\partial U} = \frac{\partial \psi}{\partial E}\left(E^{\circ}\right)\cdot\left(\sum_{i=1}^{H} W_2(i)\frac{\partial \varphi_i}{\partial r_i}\left(r_i^{\circ}\right)\cdot\sum_{j=1}^{h}\left(W_1(i,j)\cdot T(j,u)\right)\right) \tag{1}$$

Where $H -$ number of hidden neurons in the ANN model; $h -$ number of nodes in the electrical network diagram; $W_1(i,j)$– weight coefficient of connection of the j-th neuron of the input layer with the i-th neuron of the hidden layer; $W_2(i)$ – weight coefficient of the connection of the output neuron with the i-th neuron of the hidden layer; r_i, φ_i – input and output of i-th hidden neuron, respectively; E, ψ – input and output of the output neuron, respectively; r_i^0 – initial output value of the i-neuron of the hidden layer; E^0 – the initial value of the output of the output neuron; $u -$ number of unsupervised nodes (bus PQ); $T(j,u)$ – transformation matrix element.

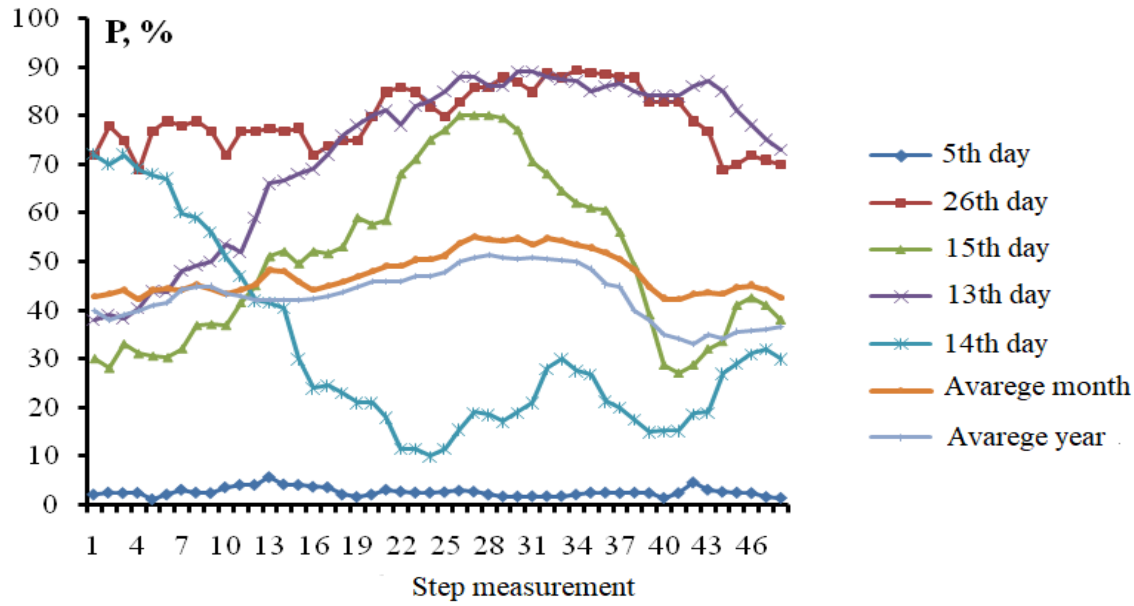


Figure 5: *Uncertainty of daily power generation wind farms on one of the typical days of the month*

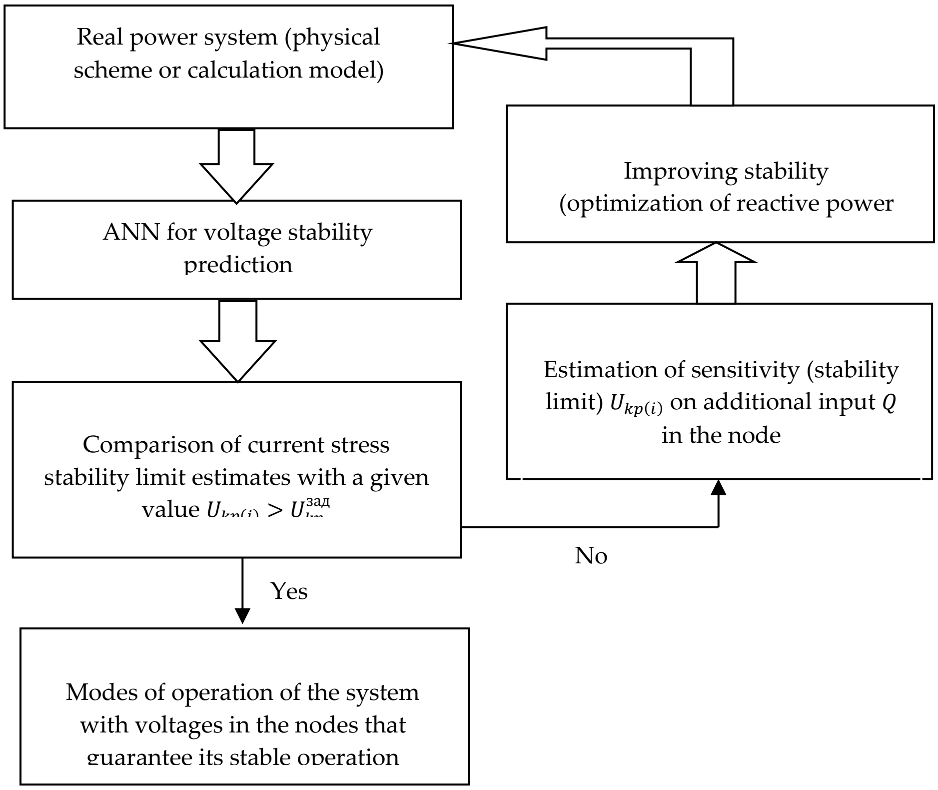


Figure 6: *Schematic diagram of monitoring the current value of the voltage stability limit using the ANN model*

Using the reduced Jacobi matrix, one can determine the sensitivity of the voltage stability limit with respect to the reactive power injection on the busbars:

$$\Delta\Pi_{U_k} = \sum_{i=1}^{N_u} \frac{\partial \Pi}{\partial U_i}\Delta U_i = \sum_{i=1}^{N_u} \frac{\partial \Pi}{\partial U_i} j_R^*(i,k) Q_{1nj,k} \tag{2}$$

$$S_k^{\Pi_u} = \frac{\Delta\Pi_k}{Q_{1nj,k}} = \sum_{i=1}^{N_u} \frac{\partial \Pi}{\partial U_i} j_R^*(i,k) \tag{3}$$

where, $N_u -$ total number of non-steered or PQ tires;
$Q_{1nj,k} -$ injection of reactive power introduced into node "k";
$j_R^*(i,k) -$ element of the reduced Jacobi matrix.

In order to increase Π_U to the desired value $\Pi_U^{\lim}$, it is necessary to introduce reactive power Q_{1nj} in the node with high sensitivity, established by the estimate from equation (3).

It should be noted that the process of improving the Π_U value by introducing additional injection reactive power must be performed for each node. In other words, equation (2) determines the final change in the value of Π_U, which is achieved by summing the reactive power injections at different nodes. At each mode point, the desired value of $\Pi_U^{\lim}$ is determined as a fraction of the current load value in p.u. or in %:

$$\Pi_U^{\lim} = \beta P_0 \tag{4}$$

where, P_0 − current mode load power;

$\Pi_U^{\lim}$ – voltage stability limit in the current mode;

β – reserv factor

In order to improve voltage stability, it is necessary to ensure effective control of the reactive power source in the nodes identified as sensitive from the analysis of the regimes of the ML stability model. The studies were carried out on a test 14-node IEEE scheme, as well as on a real scheme of the energy system of Azerbaijan.

For a 14-node scheme, training samples were obtained by calculating the flow distribution at different loads, which varied in steps of 5% from P_0 to the limiting $P_{\lim}$ in terms of load capacity. As for the samples corresponding to certain load increments, each of them is characterized by a profile and limiting stress values in terms of stability.

Table 4 shows the number of training samples, validation, and experimental use to predict the stress stability limit.

Table 4: *Parameters of the ML model for estimating the stress stability limit*

Number of training samples	Number of Validation Samples	Number of testing samples	Number of hidden neurons	Studying time sec.
1600	400	2000	15	29, 17

As can be seen from Table 5, by reactive power compensation in the network (nodes 3,6,9), it is possible to increase the system load from 290.04 MW to 613.83 MW. In this case, the total power of the compensating devices will be 248.91 MVAr.

The scientific group of ISEM SB RAS has developed a hybrid system for voltage/reactive power control in normal modes and prevention of voltage avalanche in EPS using online algorithms of ML and multi-agent system (MAS) [11]. The main idea of the development is to train and tune intelligent algorithms to recognize in a timely manner the characteristic indicators of EPS stability (coefficients of the Jacobian matrix of the steady state, L-index) in order to implement joint measures to prevent serious accidents.

Table 5: *Values of the maximum load of the system when the limit voltage is reached under the conditions of reactive power compensation*

Load power in the initial normal mode, MW	Before compensation MW		After compensation MW		Compensation nodes Π_U most sensitive to change	Optional reactive power injection, MVAr
	According to the INS model	traditional calculations oft ETAP method	According to the INS model	traditional calculations oft ETAP method		
310,8	290,0	277,2	613,8	491	3 6 9	92,04 51,37 105,5

Together with the MAS, which implements decentralized voltage regulation by changing the settings of AVR generators, to regulate reactive power sources in load nodes, a model was proposed based on online DT - an online random forest algorithm, which was trained to determine additional reactive power injections for various EPS operating modes. The basis for training the model is the results of solving a system of equations with respect to partial derivatives of the function of the sum of local L-indices, by reactive power injections

$$\frac{\partial L_{sum}}{\partial \Delta Q} = \begin{bmatrix} \dfrac{\partial L_{sum}}{\partial \Delta Q_1} \\ \cdots\cdots \\ \dfrac{\partial L_{sum}}{\partial \Delta Q_m} \end{bmatrix} = 0 \tag{5}$$

where $L_{sum} = L_1 + L_2 + \cdots + L_m$ – sum of local indices, $L = \max\limits_{j \in \alpha_L}(L_j) = \left(\frac{S_j^+}{Y_{jj}^+ \cdot U_j^2} \right)$ – global L-index proposed in [25] as an indicator of impending voltage collapse.

The proposed online random forest algorithm, PDSRF, has the ability to independently and adaptively rebuild in real time in the event of serious changes in incoming information without reducing the accuracy of identifying EPS modes. The developed intelligent system was tested both on standard IEEE circuits (IEEE 6, IEEE 118) and on a real circuit of the Bodaibo power district of the Irkutsk power system, which has problems with voltage stability.

Figure 7 clearly shows that the additional use of intelligent models based on MAC and ML, along with traditional voltage regulation by local automatics, makes it possible to maintain system stability in heavy modes and prevent voltage collapse. As a result, such a hybrid control system based on intelligent tools provides an automatic solution to the problems of secondary regulation and emergency control, thereby eliminating the human factor and ensuring the continuity of the processes of operational and automatic emergency control.

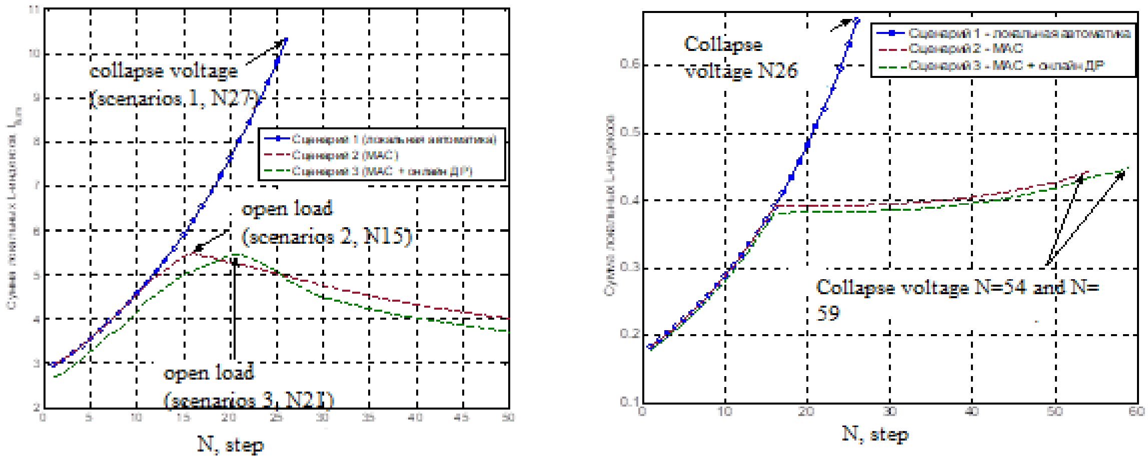


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Figure 7: *Changes L_{sum} under different control scenarios: a) IEEE 118 test pattern; b) real scheme of the Bodaibo energy district, Irkutsk region, Russia*

Conclusion

The ever-increasing saturation of modern PS with new stochastic components (high-power wind turbines, solar panels, demand management systems, etc.), the introduction of new technologies (distributed generation, flexible power transmission equipment, energy storage systems, micro-EPS, hybrid AC/DC networks, digital substations, etc.), as well as the formation of market principles of regulation, significantly complicate the tasks of forecasting and controlling the modes of modern EPS. An effective solution to this problem is the use of algorithms and ML models that are able to learn to predict and control the operating modes of the EPS, taking into account many changing factors. The results of the application of the ML technology in the tasks of operational dispatch and emergency control of EPS clearly show the prospects of such studies for subsequent practical implementation in the work of various automated control systems for electrical networks.

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