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MICROGRID MONITORING METHOD FOR PREDICTING ENERGY ANOMALIES

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Annotation: The causes of excess and shortage of electrical energy in microgrid have been analyzed. The necessity of using intelligent energy management systems for smart grids with a large component of renewable energy sources is shown. An integral part of such control systems is a network monitoring method. Based on the results of the analysis of methods for monitoring energy systems, a method for monitoring microgrids has been proposed, which allows predicting changes in flows filtering procedure integrated with the three-sigma rule. The modified filtering procedure allows real-time assessment and forecasting of the observed process, and the application of the three-sigma rule allows detection of its anomalies, since, as is known, with a normal distribution, almost all process values it a probability of 0.9973 lie no further than three sigma in either direction from the mathematical expectation. The use of this method makes it possible to formulate recommendations for managing the processes of optimal redistribution of energy flows in microsystems, to predict the risk of anomalies in energy changes in the power system.

Keywords: *smart grid, microgrid, monitoring method, Kalman filter, forecasting, non-stationary system.*

МЕТОД МОНІТОРИНГУ МІКРОМЕРЕЖ З МЕТОЮ ПРОГНОЗУВАННЯ АНОМАЛІЙ ЗМІНИ ЕНЕРГІЇ

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Анотація. Проаналізовано причини надлишку та нестачі електричної енергії в мікромережі. Показано необхідність використання інтелектуальних систем енергоменеджменту для інтелектуальних мереж з великою складовою відновлюваних джерел енергії. Невід'ємною частиною таких систем контролю є метод моніторингу мережі. За результатами аналізу методів моніторингу енергетичних систем запропоновано метод моніторингу мікромереж, який дозволяє прогнозувати зміни в процедурі фільтрації потоків, інтегрованої з правилом трьох сигм. Модифікована процедура фільтрації дає змогу в реальному часі оцінювати та прогнозувати спостережуваний процес, а застосування правила трьох сигм дозволяє виявити його аномалії, оскільки, як відомо, при нормальному розподілі майже всі процеси оцінюють його ймовірність 0,9973, лежать не далі ніж три сигми в будь-якому напрямку від математичного сподівання. Використання цього методу дає змогу сформулювати рекомендації щодо управління процесами оптимального перерозподілу енергетичних потоків у мікросистемах, прогнозувати ризик виникнення аномалій енергетичних змін в енергосистемі.

Introduction

There is currently an increase in electricity consumption worldwide. Therefore, power plants and transmission lines must be designed according to the needs of consumers. In this respect, the costs of distributed generation are lower than the costs of a power plant and expansion of the distribution and transmission system [1]. The overall strategy for the development of electricity grids is aimed at connecting the general electricity grid with microgrids [2]. This allows for increased capacity and reliability of energy supply. Distributed systems using renewable energy sources are currently developing rapidly [3]. According to this approach, hybrid systems can be used to combine more energy sources [4, 5].

The evolution of conventional power systems into smart grids allows for increased efficiency, stability and sustainability of the grid [6]. The objective factor is that the power generated by wind power plants, solar power plants, cogeneration power plants and other alternative energy sources is not a constant value. This value depends on natural conditions (the presence of wind, solar radiation activity) and other factors. In this case, such instability of renewable energy generation negatively affects the stable operation of the power system. Therefore, the classical principle of organizing the management of electric power systems is not suitable for electric power systems with a large share of renewable energy sources. In intelligent networks, special technologies and algorithms are used to organize work and control, including algorithms for predicting changes in energy in the network [7], various types of energy storage devices [8-11].

The principle of distributed generation is used to balance the load in smart grids. Within the energy and logistics clusters, the following are united: consumers of electric energy; producers of electric energy that use local solar power plants, wind power plants, gas generators, united into a shared network for generation; energy storage systems [12]. In recent years, there has been significant growth in the third component of the cluster, namely, the increase in the capacity of energy storage systems.

When building a cluster, they strive to establish a balance between producers of electric energy and systems for storage of electric energy on the one hand, and consumers of electric energy on the other. However, under conditions of increased solar and wind activity, excess electrical energy generation may be observed within the cluster. And there is a need to direct excess generated electrical energy to energy storage systems where electrical energy can be stored. Due to the operation of solar (wind) generation only during a certain period in smart grids, intelligent energy management systems are becoming a major research issue [13, 14]. In highly unstable generation and demand conditions, it is very important to assess the instantaneous state of the power grid energy balance to automatically maintain the energy balance and avoid generation deficit or overload situations.

On the other hand, in adverse weather conditions, such as reduced solar activity in winter or minimal wind speed, there may be a shortage of generation within the cluster, and there is a need to use the energy accumulated within the cluster. If the energy accumulated within the cluster is insufficient, then it is necessary to take energy from other sources, such as cogeneration power plants and nuclear power plants. Thus, workload management and resource management are two key aspects in grid computing that aim to ensure that the best services are provided to the users of the grid environment.

The above-described problem is true only for microgrids that are part of the smart grid but is also relevant for smart homes [15, 16]. Intelligent energy management systems are also used in isolated microgrids [17, 18].

Thus, there is a need for forecasting flows (effective dispatching) of the smart grid, which operates in automatic mode and allows redirecting flows of electric energy considering the needs of the consumer, considering the possibility of generation, and considering the volume of accumulated energy. There is a need for load flow optimization for the integration of smart grid components, including hybrid photovoltaic and wind power systems combined with a battery management system and unified power flow controller.

Problem statement

The aim of the work is to provide energy management and energy optimization in microgrid systems. The method of monitoring microgrids is provided by the developed method of predicting changes in flows in the electrical network based on using the Kalman filter. Based on this methodology, it is possible to formulate recommendations for managing processes of optimal redistribution of energy flows.

The main problem in solving the problem is to evaluate and predict the state of the energy source in two states:

When the amount of energy generated exceeds the limits determined by the objective need for supplied energy.

When the boundaries of optimal generation are unknown, it is necessary to determine the system's exit from the operating mode based on a given criterion.

In the first case, it is necessary to evaluate and predict the excess of a given (known) threshold of excess of the energy source “from above” or “from below”. In the second case, it is necessary to evaluate and predict the deviation of the state of the energy supply source from the operating mode.

Materials and research results

The task is to develop a method for assessing and predicting the state of non-stationary processes in the case where the analytical model of the observed process is unknown.

The following solution is proposed in the paper. For the case of discrete signal measurements, we present the signal source model in the form of an additive sum

$$S_n(t) = X_n(t) + Q_n(t), \tag{1}$$

where $X_n(t)$ – useful signal; $Q_n(t)$ – additive noise with mathematical expectation $M[Q_n(t)]=0$; R – noise variance, which is defined as

$$R=\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2; \quad \bar{x}=\frac{1}{n}\sum_{i=1}^{n}x_i \ .$$

It is known that the Kalman filter equation can be written as:

$$\begin{aligned}
&\hat{X}_n=F_n\hat{X}_{n-1}+K_n\left[Y_n-H_nF_nX_{n-1}\right]\\
&K_n=A_nH_n^T\left[H_nA_nH_n^T+R\right]^{-1}\\
&A_n=F_nP_{n-1}F_n^T\\
&P_n=A_n-K_nH_nA_n.
\end{aligned} \qquad (2)$$

Here $\hat{X}_n$ – process state evaluation vector; F_n – the transition matrix of state *n – 1* to *n*; K_n – matrix Kalman filter gain; H_n – measurement conditions matrix; Y_n – measured process value; P_n – error matrix. The index "*T*" means the transposition procedure.

The system of equations (2) can be applied directly if the matrix F_n is known, that is, if there is complete information about the process under study. As a rule, we do not have complete information about the process under study. In this case, the Kalman filtering procedure, presented in a suboptimal form, can be an assessment and forecasting tool.

We propose the following approach. We perform matrix approximation F_n at each reference point of the nth-order Taylor series. Restricting ourselves to terms of the series not higher than the nth order for each element of the matrix F_n we can write

$$F_{ij}=\begin{cases}\dfrac{j!}{i!(j-i)!}-(j-i) & 0\le i\le n,\ i\le j\le n\\ 0 & j<i\end{cases}$$

As a result, for example, for a second-order transition matrix (n=2) we obtain

$$F_n=\begin{bmatrix}1 & 1 & 1\\ 0 & 1 & 2\\ 0 & 0 & 1\end{bmatrix}. \qquad (3)$$

Since the signal itself is measured, and not its derivatives $H_n=|100|$, substituting (3) into (2) gives an algorithm for estimating X_n for the adopted approximation in the form

$$\begin{aligned}
&\hat{X}_n=\hat{X}_{n-1}+\hat{Y}_{n-1}+\hat{Z}_{n-1}+\alpha_nC_n\\
&\hat{Y}_n=\hat{Y}_{n-1}+2\hat{Z}_{n-1}+\beta_nC_n\\
&\hat{Z}_n=\hat{Z}_{n-1}+\gamma_nC_n\\
&C_n=S_n-\hat{X}_{n-1}-\hat{Y}_{n-1}-\hat{Z}_{n-1},
\end{aligned} \qquad (4)$$

here $\alpha_n=P_n^{11}R^{-1},\ \beta_n=P_n^{21}R^{-1},\ \gamma_n=P_n^{31}R^{-1}$ – filter gain matrix elements, defined through the elements P_{ij} matrices P_n, $\hat{Y}_n$ and $\hat{Z}_n$ have the meaning of estimates according to the first and second derivatives.

To implement the forecast procedure, it is sufficient to (2) choose H_n = [000] and represent the index *n* as *n=n+k*, where *k* is the number of predefined forecast steps.

Let us consider the efficiency of the proposed forecasting procedure on model data.

Fig. 1 shows a graph that shows a one-step forward forecast considering previous values.

Fig. 2 shows a histogram of the distribution of the average value of the relative forecast error, calculated by the formula

$$\Delta S=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x(i)-x(i)_{pr}}{x(i)}\right), \qquad (5)$$

here $x(i)$ – actual value, $x(i)_{pr}$ – predictive value.

From the histogram (Fig. 2), we obtain the average relative forecast error for a one-step forecast of 4.05%, according to (5).

The calculation results show that for the value of the average relative forecast errors, with an increase in the number of steps, the average relative forecast error decreases. This circumstance may be due to several reasons:

– the Kalman filter updates its estimates based on new data, and as the number of forecast steps increases, a larger number of observations are taken into account, which increases the accuracy of the forecast;

– as the number of prediction steps increases, the filter uses previous state estimates and refines the prediction;

– like many other forecasting methods, the Kalman filter, can smooth out or detect general trends in data behavior as the number of forecast steps increases. This allows the model to understand general patterns of data behavior better and reduce prediction errors [19-20].

Let us consider the application of the proposed estimation and forecasting method to detect changes in energy flows of electrical networks.

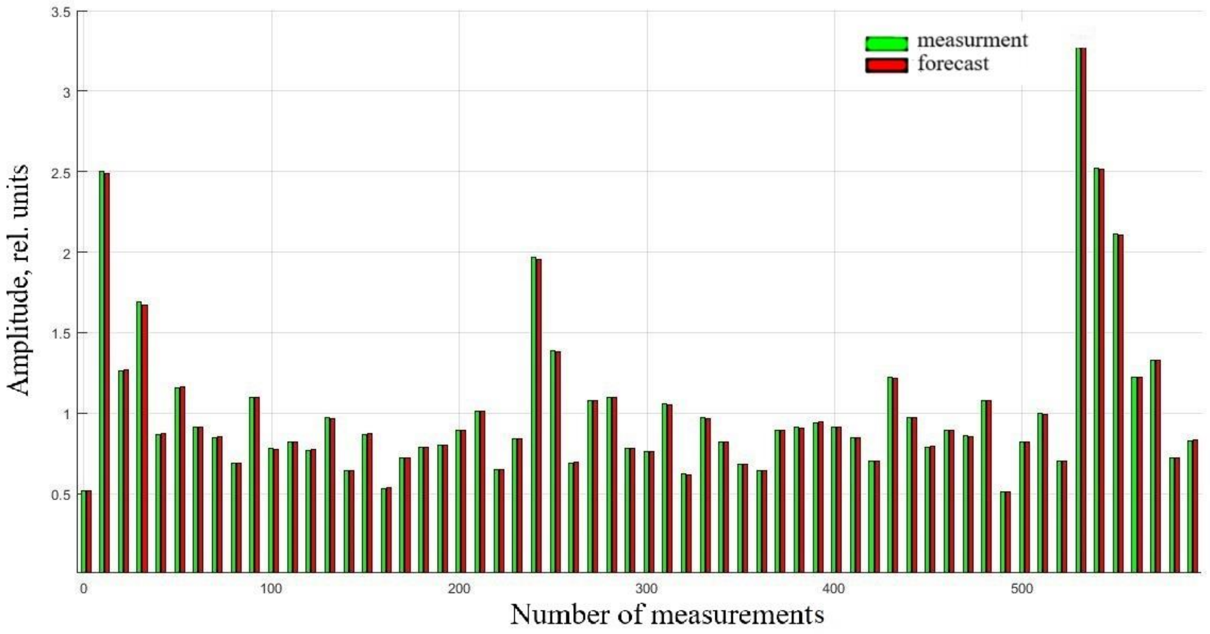

Fig. 1. One-step-ahead forecast histogram considering previous values

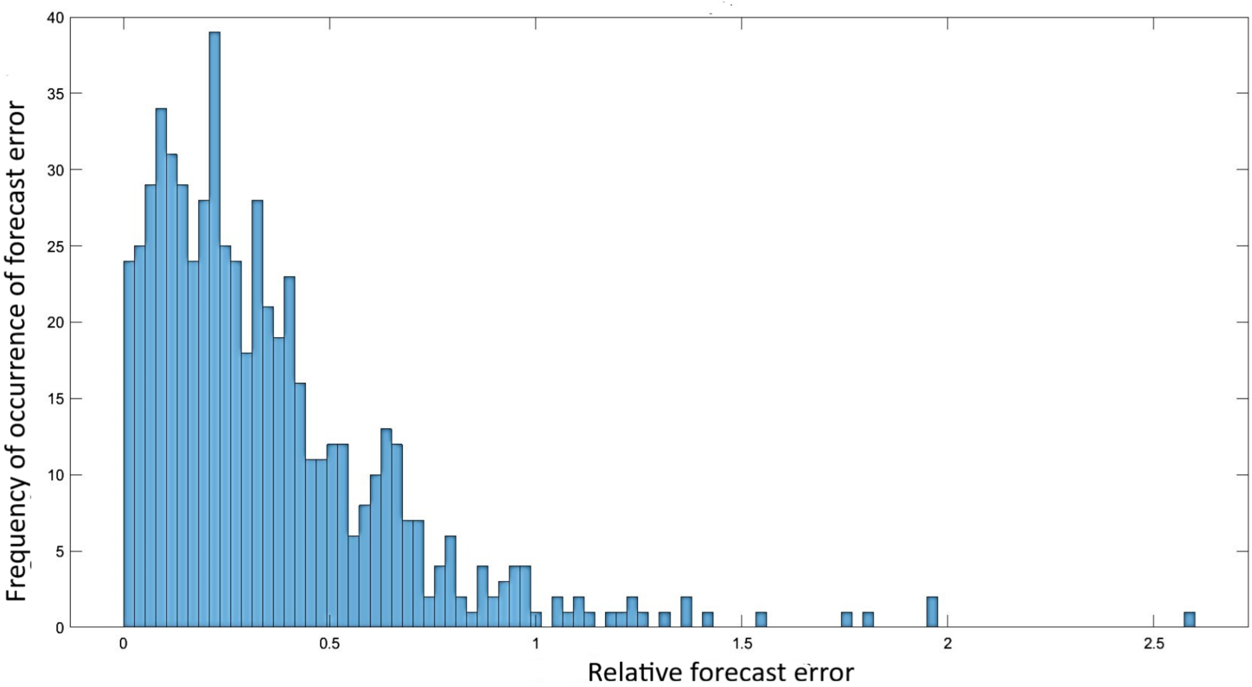

Fig. 2. Histogram of the distribution of the average value of the relative forecast error

As already mentioned, two cases are possible.

In the first case, the current value of the energy in terms of modulus exceeds the previously set permissible value. In this case, it is necessary to predict and detect this event to redirect excess energy for its conservation or, conversely, to fill the energy shortage from the existing source. In the second case, it is necessary to detect an anomalous deviation of the energy source from its average value.

For the first case, it is proposed to use the procedure for calculating statistics of this type:

$$B_M = \sum_{l=1}^{M} b_l, \quad B_0 = 0, \quad l = 1,2,\ldots,M \tag{6}$$

$$b_l = \operatorname{sgn}(S_l - \hat{X}_l) = \begin{cases} +1, & S_l - \hat{X}_l \geq 0 \\ -1, & S_l - X_l < 0 \end{cases} \tag{7}$$

on the interval (*n-M, n*). The values (B_M - *min*B_M) and (*max* B_M - B_M) determined in this interval are compared with the given threshold *h* modulo. Thus, we set the threshold value *h* as the number of deviations with the same plus or minus sign. Then, the result is compared with the specified number of deviations (threshold). When the threshold value h is exceeded by one of these values, a decision is made about the source's excess or shortage of energy in the electrical network, and appropriate actions are taken to redirect energy.

In the second case, it is necessary to determine the anomalous deviation of the energy source value from the average value, i.e. from the operating mode.

To solve the problem, it is proposed to use the so-called three-sigma rule. The three-sigma rule is used to identify anomalies in stochastic time series data. In this context, this method allows you to detect values that deviate significantly from the expected range and are based on the characteristics of the data distribution.

In this work, we use this method, integrating it with a modified Kalman filtering and forecasting procedure. Thus, the final overall algorithm developed is as follows:

Evaluating the current value $\hat{X}_l$ based on the system of equations (2) considering expression (3) and the standard deviation σ (standard method).

The statistics B_M are calculated from expression (6) considering (7).

The control limit values are compared with the threshold $h = 3\sigma$.

If the value *h* of one of the control limit values is exceeded, a decision is made to detect an anomaly and take appropriate control action.

Figure 3 shows a graph illustrating the operation of the proposed modified forecasting algorithm based on the Kalman filter with a built-in anomaly detection function using the three-sigma rule. In Fig. 3, real measurements are shown in green, predicted values in red, and detected anomalies in energy changes in pink. As seen from Fig. 3, integrating the proposed Kalman estimation and forecasting algorithm with the three-sigma rule allows for the effective identification of anomalous values of the time series. Thus, we obtain a reliable tool that allows us to use it to detect anomalous deviations in energy flows to optimally manage these flows. Redirect excess energy either into battery energy storage systems [19] or into hydro energy storage [20], or into gravity storage [21-25]. The latter type of energy storage is a promising mechanical energy storage technology and offers significant advantages, especially in areas with limited water resources, where there is no available space for hydro energy storage. Gravity-based energy storage systems can be economically feasible when locating a microgrid near abandoned mine workings.

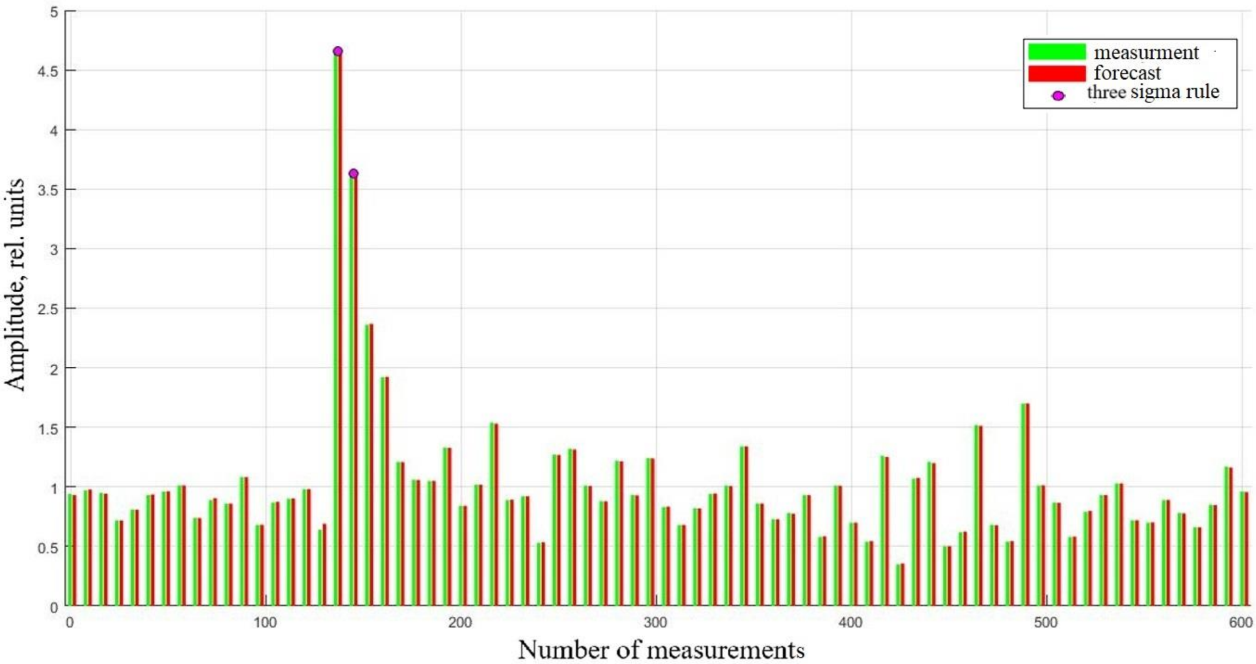

Fig. 3. Detection of energy change anomalies

Conclusions

1. The developed method for assessing and forecasting energy flows in electrical networks is invariant to the nature of the studied stochastic non-stationary processes .
2. The proposed method enables the efficient detection of anomalies in the studied processes in real time and can be used in energy flow control systems in electrical networks.
3. Integrating the proposed method into automation systems of energy enterprises in the form of structural and algorithmic components will ensure their hardware, design and software compatibility.
4. This approach to load forecasting in the electrical network allows for the automatic timely directing of energy

flows to consumers, thereby effectively using renewable energy sources while considering the availability of such stable generation sources as nuclear power plants. Moreover, the developed flow forecasting methodology allows for the use of not only battery energy storage systems but also gravity-based energy storage.

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