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Power Forecast of Renewable Energy Power Plant Based on Kalman Filter Method

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Abstract. At present, the prediction accuracy of water power plant is poor. In order to improve the prediction accuracy of water power plant. Firstly, the regression sliding model is obtained by analyzing the power sequence of the water power plant, and the regression sliding model is regarded as Kalman filter method. Then, the equation value is obtained by the state equation of Kalman filter method, and the power generation is predicted by Kalman filter method. In the follow-up case analysis, the evaluation index of the China Energy Bureau is used to evaluate the prediction accuracy of power generation. The MATLAB prediction results show that the proposed method in this paper can get better results and higher prediction accuracy.

Key words. Kalman Filter, Renewable Energy, Power Generation by Power Plant, Power Prediction.

1. Introduction

Under the constraints of a low-carbon economy and environmental protection, the energy consumption problem becomes increasingly severe in the production process of different fields, so it is particularly important to vigorously develop and popularize renewable energy. Among renewable energy sources, solar energy has a wide range of applications and the characteristics of green environmental protection, which can be used by using local materials. Reducing energy consumption can also save on the economic costs of energy transportation and energy exploitation. In the rational utilization of new energy, photovoltaic power generation is the most common utilization mode of new energy. From a broad point of view, photovoltaic power generation is a very important part of renewable energy power generation, which has a relatively low cost and can adjust the size of the photovoltaic array through the dynamic changes of load. With the emergence of intelligent algorithms, the operation mode is also changing, from the original distributed operation mode to the operation mode of grid-connected photovoltaic power plant. In the process of grid-connected photovoltaic power plant operation, it is necessary to reasonably predict the power generation of the power plant to prevent the safe operation of the power plant from being affected by external factors and conditions. The photovoltaic power plant operation mode is very prone to intermittent power supply, thus reducing the stability of power grid operation. Therefore, the research on power generation prediction of water power plants is of great significance for the stable and safe operation of water power plants, and can provide effective support for the prediction of new energy photovoltaic power generation.

Regarding new energy photovoltaic power plant power forecasting, the research specifically involves two aspects of forecasting content, single-point forecasting and interval forecasting. There is much research on single-point prediction of new energy photovoltaic electric generation, and prediction models and data collection mostly cause the errors of single-point prediction. In order to reflect the output characteristics of new energy photovoltaic electric generation more comprehensively and reduce the decision-making risks of various dispatching plans in the water power grid, relevant researchers have carried out comprehensive research on the output power of new energy photovoltaic electric generation, including single-point prediction of new energy photovoltaic electric-generation and interval prediction of new energy photovoltaic electric-generation. Reference [1] specifically uses the historical data of illumination, uses a neural network to predict the illumination intensity, and calculates the electric generation of new energy photovoltaic power plant from the illumination intensity and environmental temperature parameters. According to the historical data of new energy photovoltaic electric-generation, the new energy photovoltaic system is a black box, and the electric-generation prediction of power plant is realized by constructing the new energy photovoltaic electric-generation system model. Literature [2] uses BP neural network model to predict the electric generation of new energy photovoltaic power plant. The total solar radiation, ambient temperature, and horizontal scattering radiation are taken as the input of the electric-generation prediction model, while photovoltaic electric generation is taken as the output, thus realizing the electric-generation prediction of new energy photovoltaic power plants. And the advantages and disadvantages of different generation power prediction methods mentioned in the above documents, this paper constructs a real-time generation power prediction of water power plants based on Kalman filter method [3]. Through the mechanism of Kalman filter method in the generation power series prediction of power plants, a new rolling time series generation power prediction method is proposed on the basis of existing power prediction to realize the generation power prediction of power plants. Finally, the Kalman filter method is used to improve water power plants' generation power prediction performance.

2. Basic Description of Kalman Filter Algorithm

A. Kalman Filter Principle

The mathematician Kalman introduced a spatial model into the filter theory and extrapolated to the recursive estimation algorithm, which was named Kalman filter theory. In the field of mathematical methods, Kalman's algorithm is a class of recursive estimation prediction algorithms. The minimum variance without bias is used as the calculation rule to obtain the optimal estimate value of the estimation system, and the algorithm has excellent effectiveness and anti-noise effect. The Kalman filter is a linear stochastic system formed by the equation of state and the observation equation, and the filter is described by the state space model of the system.

The system equation of state uses the principle of ground inference, takes the minimum mean square deviation without deviation as the estimation rule, and obtains the optimal estimated value of the system through the recursive algorithm acting on the state variables of the filter. Using the state space model of noise and signal, the value of the current moment and the value of the previous moment are used as the basic values, and the estimated value of the state quantity is updated, and the updated estimated value of the current moment is calculated. Kalman's recursive order can describe the "estimated measurement-actual measurement-correction value", through the above recursive operation processing, the observation value under the random system can be quantitatively inferred, and the minimum mean square deviation value is used to estimate the measured value correctly as much as possible (Figure 1).

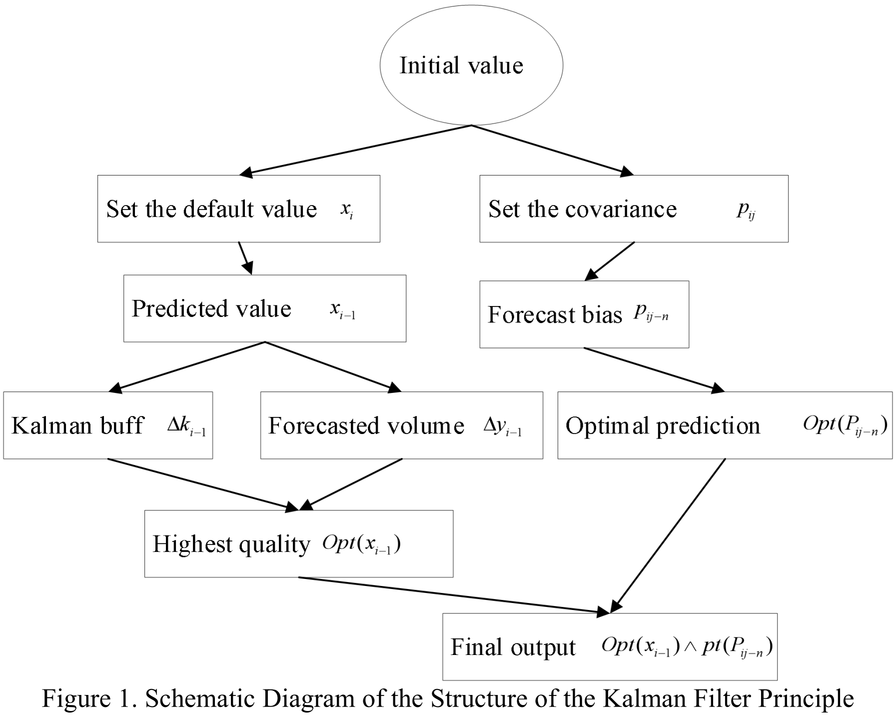

Figure 1. Schematic Diagram of the Structure of the Kalman Filter Principle

B. State Space Model

In his research, R.E. Kalman proposed the state-space method, and the main core ideas of this theory can be described in the following three points: introduce the concept of state variables; Establish an equation of state to describe the process of state change of the system. Set the observation equation for the state of the system and observe the system through the equation.

The state space model is mainly applied to the optimal filtering problem, which is the difficult problem of filtering the filtering problem by screening and filtering out the noise in the noise pollution, and obtaining the real signal after filtering out the noise with the maximum probability, or obtaining the optimal estimation state of the system, and obtaining the best estimation is the difficult problem of the filtering problem. Objects moving at high speeds, such as spacecraft and rockets, have great interference with their trajectories in the forced movement. In the field of engineering, linear control technology can be used to describe the trajectory of the motion of similar objects through mathematical equation expressions. However, in many engineering problems, some cases cannot be described in the form of functions or mathematical expressions, and state variables cannot be prepared to be expressed. For example, the position and operating speed of the spacecraft cannot be directly measured to obtain its state variables, so more sophisticated instruments need to measure it, and then obtain the optimal state data. However, in many measuring equipment such as radar and other instruments, there are random interference and other phenomena in themselves, and most of the data obtained are interference information data, and the correct information value is obtained from the above-mentioned error data, and the signal data needs to be obtained by precision instrument and equipment observation, and then the state variable data is predicted or calculated, and the optimal control rule of the system is obtained.

A state-space model that describes a general linear discrete system can be illustrated in Equations (1) and (2):

$$x(t+1) = Ax(t) + \phi w(t) \tag{1}$$

$$y(t+1) = Hx(t) + v(t) \tag{2}$$

In equation (1) and equation (2), equation (1) is the equation of state, equation (2) is the measurement equation, and the state of the system at time $t+1$ can be described by ; $x(t+1)$ The measured value at time $t+1$ is $y(t+1)$. The system noise of the covariance matrix Q is represented by $w(t)$; The measured noise of the covariance matrix R is represented by . $v(t)$ Set the two systems to be Gaussian white noise and do not interfere with each other; The system parameters are represented by F and M, and for the multi-model system in this paper, they represent the matrix. The measurement system parameter is H, and for the multi-measurement system in this paper, H is also a matrix.

C. Kalman Filter Algorithm

Combined with the state space model, the Kalman filter theory can deduce the Kalman filter algorithm, and the algorithmic thinking is the core part of the prediction model, and the Kalman filter algorithm can be used to establish the power prediction model of new energy hydro power station based on the Kalman algorithm.

(1) Calculate to obtain the predicted measurement $\hat{y}(t+1/t)$

After obtaining $y(0)$, $y(1)$ $y(t)$ assuming that the predicted value of the state vector $x(t+1)$, $\hat{x}(t+1/t)$ has been found, the predicted value of the system state at time t 1 is calculated according to equation (3):

$$\hat{y}(t+1/t) = H(t)\hat{x}(t+1/t) + v(t) \tag{3}$$

(2) The optimal linear estimate is calculated

After obtaining the systematic observation value , the predicted data value can be adjusted and corrected, and the best linear calculation estimate value can be obtained. In order to obtain the best-optimized observation value in the end, it can be set to use the updated observation value in the system to obtain new data information:

$$\hat{x}(t+1/t+1) = \hat{x}(t+1/t) + K(t+1)\dot{y}(t+1/t) \tag{4}$$

In formula (4):

$$\dot{y}(t+1/t) = H(t+1)\dot{x}(t+1/t) \tag{5}$$

Combining the above equation (4) and equation (5):

$$\dot{x}(t+1/t+1) = \dot{x}(t+1/t) + K(t+1)H(t+1)\dot{x}(t+1/t) \tag{6}$$

Equation (6) is the modified description equation for the optimal linear estimation of the system, where the optimal gain function is $K(t+1)$.

3. Proposal of Power Prediction for Waterpower Plants

A. Initial Multi-Dimensional State Analysis of Power Plant

According to Kalman filter algorithm, the initial power state of the power plant can be predicted $X(k)$, and the multidimensional n operation state is discrete. Assuming that the state vector represents the prediction dimension $A(k+1,k)$ of electric-generation of water power plant $\omega(k)$, the transition matrix represents the algorithm state, $B(k+1,k)$ the noise vector represents the water power plant and the transition matrix represents the algorithm excitation, the initialization of multi-dimensional state can be expressed as formula (7).

$$X(k+1) = A(k+1,k)X(k) + B(k+1,k)\omega(k) \tag{7}$$

Among them, the multi-dimensional state needs to be planned on the corresponding side $Z(k+1)$, and the transition matrix should be constructed *m*, If the observation vector represents the prediction dimension of water power plant $Z(k+1)$, the transfer matrix represents the prediction output of the water power plant $v(k+1)$ and the noise vector represents the measurement Kalman filter algorithm, it can be expressed by formula (8).

$$Z(k+1) = C(k+1)X(k+1) + v(k+1) \tag{8}$$

However, after the multi-linear numerical expression in formula (2), the optimal value should be predicted, and the theoretical prediction result of water power plant generation power is $\hat{X}(k+1|k+1)$, then the optimal filtering estimation equation is expressed as formula (9):

$$\hat{X}(k+1|k+1) = A(k+1,k)\hat{X}(k|k) + K(k+1) \tag{9}$$

Among them, gain analysis should be carried out on the prediction results. The gain analysis appears in the form of a matrix, so the optimal gain matrix equation for electric-generation prediction of water power plants is expressed as formula (10):

$$K(k+1) = P\left(k+1, k\right) C^T(k+1) \tag{10}$$

However, water-electric generation involves output, output, energy transformation and other issues. To ensure the transformation among various indicators, collaborative analysis is needed [4]. Then, the error-free covariance equation of single-step prediction of water power plant generation power prediction is expressed as formula (11)

$$P(k+1, k) = A\left(k+1, k\right) P(k, k) \tag{11}$$

Combined with formula (4) and formula (5), the final result of electric-generation prediction of water power plant can be optimized, and the covariance equation of Kalman filter prediction error is expressed as formula (12)

$$P(k+1, k+1) = \left[I - K\left(k+1\right) C\left(k+1\right)\right] P(k+1, k) \tag{12}$$

Among them, the gain matrix of Kalman filter algorithm *K* and the covariance matrix *P* of algorithm error are represented.

B. Observation and Description of Power State of Water Power Plant

Regression model identifies the state equation of electric-generation prediction of water power plant. The current time value of the time series can be expressed as a linear combination of the time value and the noise series as formula (13)

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t \tag{13}$$

The state equation and observation equation of Kalman filter algorithm obtained from formula (14) are expressed as follows:

$$\begin{Bmatrix} X_1(k+1) \\ X_2(k+1) \\ \vdots \\ X_p(k+1) \end{Bmatrix} = \begin{Bmatrix} \varphi_1 & \varphi_2 & \cdots & \varphi_p \\ 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & 0 & 1 & 0 \end{Bmatrix} \omega(k+1) \tag{14}$$

Where 1 stands for distributed convergence and 0 stands for continuous electric-generation, so the set is $Z(k+1)'$.

$$Z(k+1)' = (1 \quad 0 \quad \cdots \quad 0) \begin{Bmatrix} X_1(k+1) \\ X_2(k+1) \\ \vdots \\ X_p(k+1) \end{Bmatrix} + v(k+1) \tag{15}$$

Where 1 stands for distributed convergence and 0 stands for continuous electric-generation, so the set is.

C. Proofreading and Constraint of Generation Power Forecast of Water Power Plant

According to the relevant regulations of China's Energy Bureau, the prediction time of electric generation of power plant is 15 minutes to 4 hours, so the prediction of electric-generation of a power plant should be intermittently sampled with a time interval of 15 minutes [6], X_t and *p* the number of predictions in one cycle is 16. After the prediction is completed, the prediction results should be proofread. Because it is necessary to forecast the electric-generation of water power plant, this paper puts forward a rolling model based on time series on the basis of analysis. In the process of forecasting the electric-generation $\varphi_1 \cdots \varphi_p$ of power plant X_{t+1}, X_t needs to use several numerical values and prediction parameters. When forecasting the electric-generation, $X_t \cdots X_{t+15}$ will be regarded as the actual value, and the prediction parameters $\varphi_1 \cdots \varphi_p$ will roll forward from iteration to $\varphi_2 \cdots \varphi_{p+1}$, thus realizing the tracking prediction and prediction of the electric-generation $B(k+1)'$ of water power plant. Therefore, the proofreading of the prediction is shown in Formula (16).

$$B(k+1)' = \sum Z(k+1)' \cdot X_t \cdot \varphi_t \tag{16}$$

At the same time, the proofreading results should be constrained, as shown in Formula (17).

$$B(k+1)' = Q(k) \cdot R(k) \sum Z(k+1)' \cdot X_t \cdot \varphi_t \tag{17}$$

Among them, in the process of water power plant, $Q(k)$ and $R(k)$ is composed of prediction error covariance of the prediction method. In the prediction equation of water power plant based on Kalman filter algorithm, $X(k+1)$ the representation is the next prediction value, which is unknown. Therefore, $Z(k+1)$ the optimal filtering estimation equation cannot be obtained. Therefore, the predictive recursion equation must predict the electric-generation of water power plants. In this paper, $Z(k+1)$ the observation point is selected as the prediction equation of water power plant electric-generation, and the optimal solution is sought in the prediction model and learning according to the priority electric-generation sequence samples X_{t+1}, so as to obtain the optimal generalization ability [7].

D. Adjustment of Prediction Error

The prediction-value of water power plant is measured by using the evaluation indexes in the power prediction management, the accuracy of the daily average power plant power prediction plan of daily average power plant power prediction plan curve and all-day power plant power prediction structure, so the accuracy of daily average power plant power prediction plan curve is as follows:

$$r_{ij} = \left[1 - \sqrt{\frac{1}{16}\sum_{k=1}^{16}\left(\frac{P_{Mi}^{k} - P_{Pi}^{k}}{C_{ap}}\right)^{2}} \right] \times 100\% \tag{18}$$

It is the calculation accuracy of different stages, in which the initial accuracy is:, the qualified rate of the daily average electric-generation prediction plan curve is:, and the comprehensive accuracy is.

r_{ij} is the calculation accuracy of different stages, in which the initial accuracy is: $r_{11} = \frac{1}{96}\sum_{i=1}^{96} r_{1i}$, the qualified rate of the daily average electric-generation prediction plan curve is: $r_{22} = \frac{1}{16}\sum_{k=1}^{16} B_i^k \times 100\%$, and the comprehensive accuracy is $r_2 = \frac{1}{96}\sum_{i=1}^{96} r_{2i}$.

The overall accuracy of the integrated water power plant r_{ik} indicates the qualified rate of the generation power prediction of the second water power plant.

$$r_{ik} = \sqrt{\frac{1}{96 \times 16}\sum_{i=1}^{96}\sum_{k=1}^{16}\left(\frac{P_{Mi}^{k} - P_{Pi}^{k}}{C_{ap}}\right)^{2}} \times 100\% \tag{19}$$

Among them, r_{1i} it indicates the accuracy of the generation power prediction of the second water power plant, P_{Mi}^{k} the actual generation power in the generation power prediction process of the first water power plant [8], [9], P_{Pi}^{k} the predicted generation power in the generation power prediction process of the first water power plant and C_{ap} the startup capacity of the water power plant [10], [11].

4. Forecast Analysis

Based on the Kalman filter theory, the power prediction model of the new energy power station is constructed, the state X and variance P at the initial moment are set, the state parameters and variance parameters at the next time are obtained, and the optimal state estimate S is obtained by introducing the program loop calculation. The program prediction is realized in the MATLAB simulation platform, and the data values of the initial motion state variables and the optimal state estimate are entered. In this paper, the application effect of Kalman filter method is analyzed by using real data samples of hydro power plants.

A. Forecast Preparation

The data used in this forecast comes from a water power plant in a city. The capacity of the water power plant is 200MW, and each unit is equipped with an electric-generation module bracket. According to the meteorological data of local weather plants, the location of water power plants is rich in light and wind energy resources, which have certain development values. Taking the transmission capacity of the distributed power grid as an independent variable, the electric-generation of the power plant is predicted. In this forecast, the data from December 2021 to July 2022 are selected as the forecast data samples, and the forecast data set is established. Divide the data into data samples and data to be predicted, and the details are shown in Table 1.

Table 1. Predictive Test Data

Group	Different Data Sets	Time Series of Data
Theoretical Test	Sample Training Set	Exclude the data from 9:00 to 17:00 on July 14, 2022
Actual Monitoring	Forecast Data	From 9:00 to 17:00 on July 14, 2022

According to the previous forecasts, the power convergence of distributed power grids has a great impact on the prediction results of water power plants. Therefore, in this study, the data samples are classified, and the data are divided into two types: partial fusion and comprehensive fusion by statistical software. The detailed statistical results are shown in Table 2.

Table 2. Analysis Results of Local and Normal Data Samples

Data set	Local	Holistic
Theoretical test	December 1-December 8, 2021, December 10-13, 2021, July 1-July 19, 2022, July 22-July 30, 2021	December 9, 2021, July 20-21, 2022
Actual monitoring	July 14, 2022, 7:00-12: 00	July 14, 2022, 7:00-12: 00

In order to better complete the analysis of the prediction results of water power plants, the relative error-index and evaluation results are set, and the results are shown in Table 3.

Table 3. Value Range of Prediction Index and Results of Prediction Evaluation

Rank	**1**	**2**	**3**	**4**
Index value range	0-5	5-10	10-15	15 Up
Evaluation results	Better	Good	General	Poor

Using the above indicators to analyze the prediction results of water electric-generation, divide the test day into hours as a cycle, predict the electric-generation in each hour, and complete the analysis of the prediction method of electric-generation. In this prediction, the neural network prediction method, iterative power flow prediction method and Kalman filter method proposed in this paper are selected to predict the predicted data, and to determine the application effect of the proposed methods.

B. Fusion Results of Power Generated by Water Power Plants

According to the above contents, the fusion results of the electric-generation of the power plant on sunny days are analyzed by using the Kalman filter method proposed in this paper, the neural network prediction method and the tidal flow iterative prediction method, and the analysis results are shown in Figure 2.

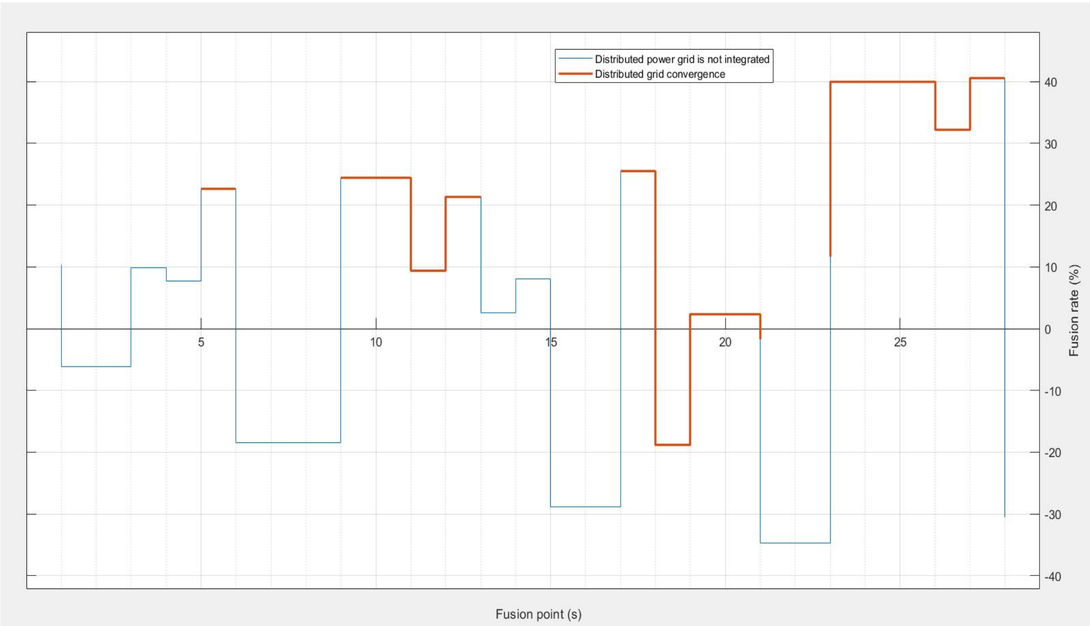

Figure 2. Fusion Results of Electric-generation of Water Power Plants

By analyzing Figure 2, it can be seen that there is little difference between the result of water power plant generation power convergence and the actual water power plant generation power in the prediction process, and the overall water power plant generation power prediction result is close to the actual water power plant generation power, and the difference of power fusion is also relatively small.

C. Power Flow Adjustment Results at Different Distribution Points

The adjustment results of power flow, and the prediction results of different methods are analyzed according to relative errors, which are shown in Figure 3.

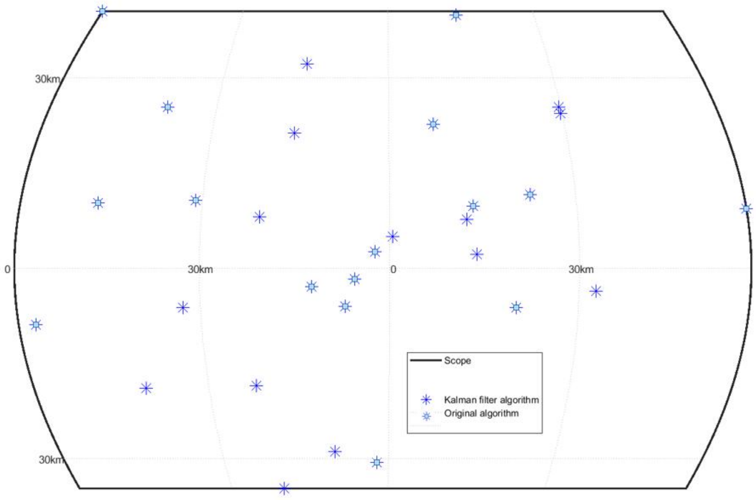

Figure 3. Comparison of Power Prediction Accuracy of Water Power Plants

By analyzing Figure 3, it can be seen that the overall accuracy of the two methods is quite different. The results of comparing different positions are shown in Table 4.

Table 4. Accuracy of Power Flow Adjustment by Two Methods [Unit:%]

Test method	Accuracy	Error rate	Volatility
Neural network algorithm	97.32±1.32	2.35±0.53	10.52±0.72
Kalman filtering method	96.83±0.95	4.65±0.23	20.42±0.24
Significance = 32. 885			

The average relative error is analyzed in this paper. The adjustment rate of water electric-generation power flow using Kalman filter method is 2.5%, while the adjustment rate of water electric-generation power flow using neural network algorithm is 3.6%, and the relative error of water electric-generation electric-generation prediction using iterative power flow algorithm is 4.1%. The relative error results of water electric-generation power flow adjustment results of different methods are determined. The prediction accuracy of local water electric-generation electric-generation prediction results of different prediction methods is relatively high, but the algorithm proposed in this paper obviously differs among different methods.

D. Prediction Error Analysis

Figure 4 illustrates the power prediction error results based on numerical weather prediction system data. From the distribution of the curve, it can be seen that the error curve fluctuates greatly, indicating that the prediction error is relatively large, which is due to the limitation of the accuracy of the numerical weather prediction prediction prediction data, and the error is relatively significant.

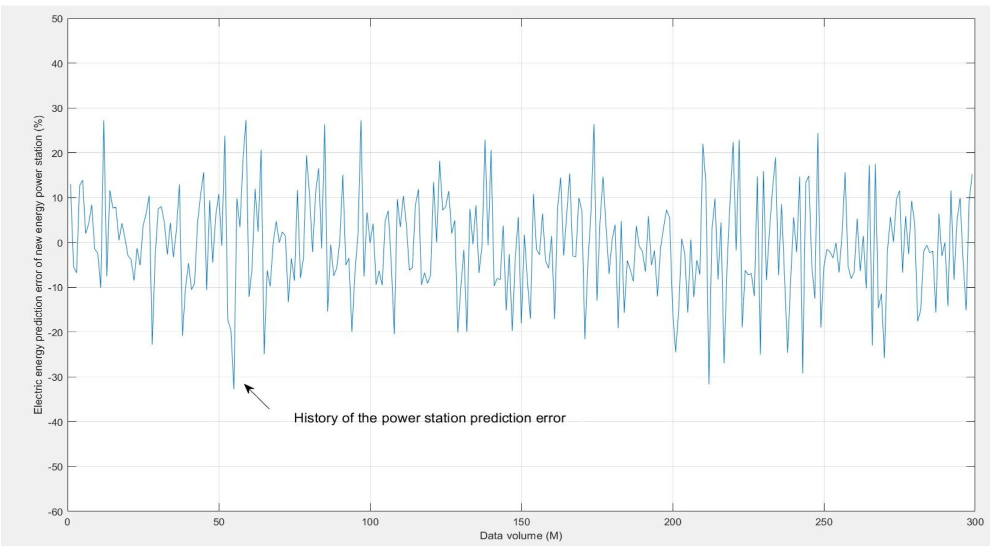

Figure 4. Description of Prediction Results based on Numerical Weather Prediction System

Figure 5 shows the results of the power prediction error based on the Kalman filter. It is evident from the variation in the curve that the curve fluctuates sharply but for a short duration at the beginning of the power forecast, as the initial value is set to zero. With the successive iterations of the model, the prediction error decreases rapidly and gradually tends to be stable, fluctuating within a certain controllable range. This indicates that the prediction is quite effective and that the actual measurements can be effectively tracked. Compared with the power prediction error results based on numerical weather prediction system data, the prediction accuracy is significantly improved.

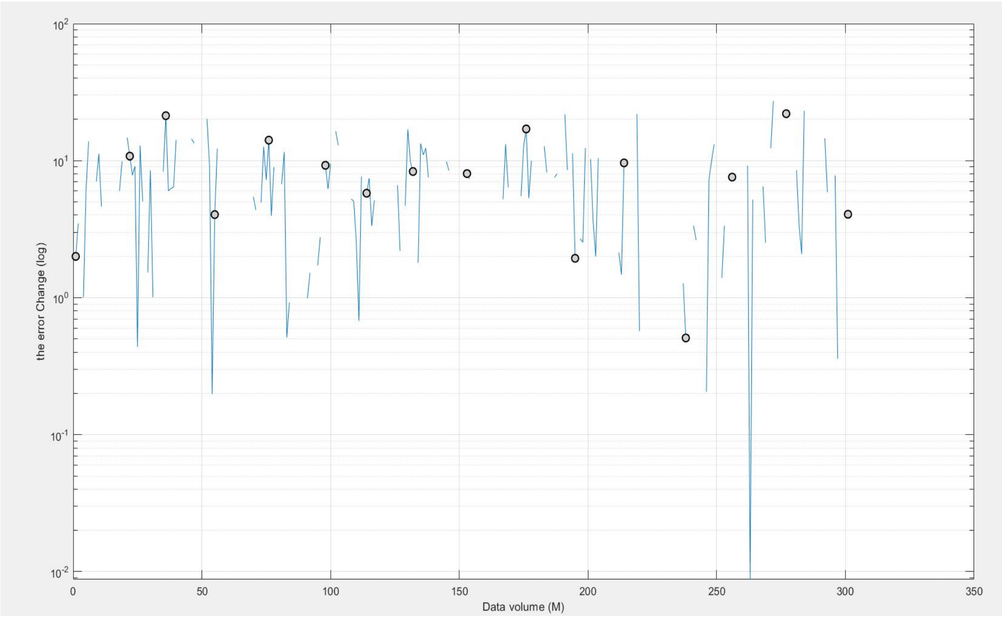

Figure 5. Description of Power Error Results of New Energy Power Station based on Kalman Filter Algorithm

E. Analysis of Overall Forecast Results of Generating Power of Water Power Plant

According to the prediction conditions of distributed power plants, the data of the whole distributed power plants are taken as the prediction basis, and the original prediction methods of Kalman filter method proposed in this paper are compared to judge the prediction results of electric-generation power of distributed power plants. The analysis results are shown in Figure 3.

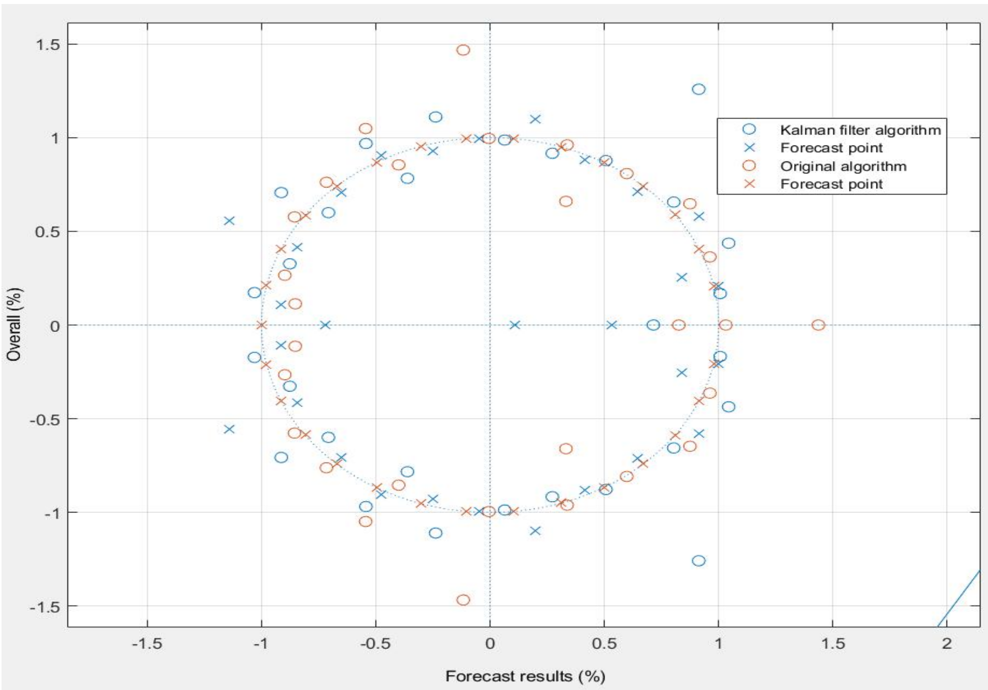

Figure 6. Forecast Results of Electric-Generation of Whole Distributed Power Plant

By analyzing Figure 6, it can be seen that the prediction results of electric-generation by different methods are quite different from the actual electric-generation by power plant. The electric-generation prediction of power plant using the Kalman filter method proposed in this paper is close to the actual electric-generation of power plant, while the electric-generation prediction results using the other two comparison methods are distorted. The data in the figure are counted, and the prediction accuracy of water power plant with different methods is analyzed, which is shown in Figure 7.

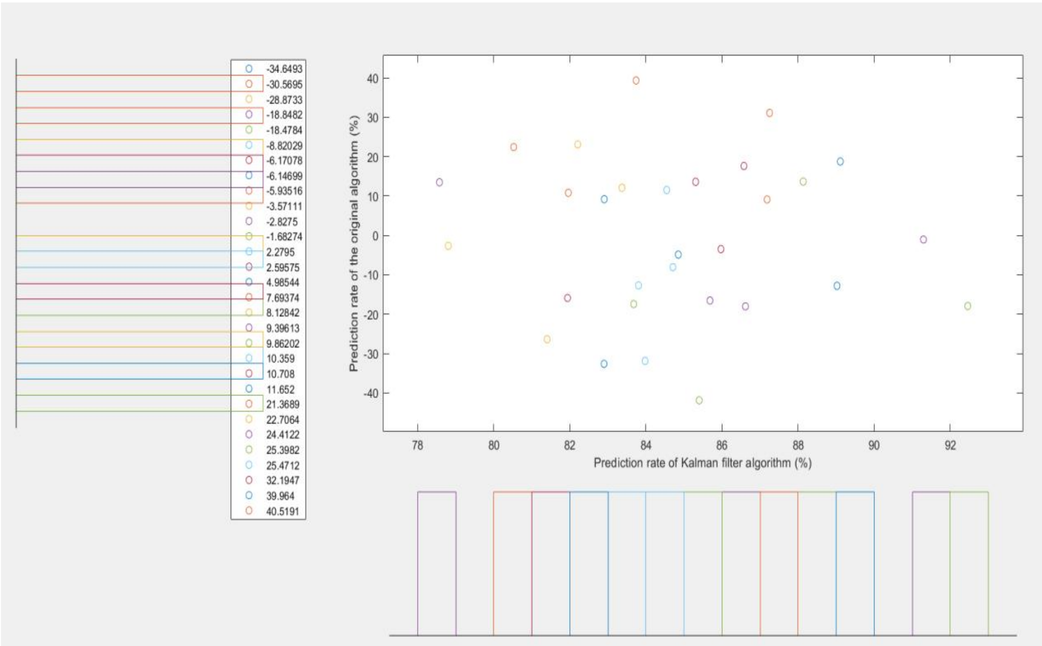

Figure 7. Comparison of Prediction Accuracy of Generation Power of Whole Distributed Power Plant

Figure 7 analyzes the prediction accuracy of electric-generation of water power plants at different time points, and in Figure 4, the prediction accuracy of electric-generation power of water power plants at different times using the Kalman filter method proposed in this paper is better than that of the other two comparison methods. The accuracy of the proposed method is 92%, the relative error of the neural network method is 40%, and the relative error of the electric-generation prediction of the water power plant is 8.7%, which indicates that the algorithm proposed in this paper has high accuracy and feasibility, and is suitable for the electric-generation power prediction of water power plants.

5. Conclusion

Due to the fluctuation and intermittency of power generation in hydro power plants, it is necessary to predict the power generation power of power plants when dispatching hydro power plants to reduce the impact of grid-connected power generation systems on the stable operation of the power grid. Therefore, this paper studies the prediction of power generation of hydro power plants, proposes a prediction method for power generation of hydro power plants based on Kalman filter method, expounds the principle of Kalman filter method with the state model, analyzes the prediction mechanism of Kalman filter method for power generation series, and compares the prediction methods of power generation of different hydro power plants through prediction. Experimental results show that the proposed method can effectively improve the prediction accuracy and have high feasibility when applied to the prediction of hydro power generation in hydro power plants. Among them, the power flow adjustment rate of the proposed method is 2.5% and the prediction accuracy is 92%, while the power flow regulation rate of hydro power plants based on the neural network algorithm is 3.6%, and the relative error of power generation prediction results based on power flow iteration algorithm is 4.1% and the prediction accuracy is 40%. It provides a guiding experimental method for the power prediction research of new energy power stations.

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Research and demonstration application of key technologies of new base data center.

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