

Article

Quantification of Power Grid Frequency Regulation Capacity Demand Based on Deviation Prediction

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Abstract

Driven by global decarbonization goals, the rapid growth of renewable generation is increasing the frequency-regulation burden on power systems. Reliable estimates of regulation-capacity demand are therefore essential for coordinated energy and ancillary-services market clearing and secure grid operation. We develop a data-driven method that captures renewable variability while quantifying this demand accurately. The method uses renewable output, load fluctuations and meteorological conditions as predictors, with the maximum one-minute net-load deviation over each interval defining the target capacity. To address scale imbalance and redundant high-dimensional inputs, we introduce a dual screening procedure for training samples and features based on an improved weighted Euclidean distance. A deep neural network (DNN) then produces deterministic capacity forecasts, while adaptive-bandwidth kernel density estimation (ABKDE) models their residual errors. The upper confidence bound of the resulting prediction interval is used as the required regulation capacity. Tests on 2023 operating data from a provincial power grid yielded a spring-scenario mean absolute percentage error (MAPE) of 3.62% and a coefficient of determination (R^2) of 98.31%. With ABKDE compensation, prediction-interval coverage probability reached 100%, while the prediction-interval normalized average width (PINAW) remained 7.46%. Performance remained robust across renewable-penetration levels and all four seasons.

Keywords: electricity market; frequency regulation capacity; data-driven; demand quantification



Academic Editor: Bo Yang

Received: 11 August 2026

Revised: 17 September 2026

Accepted: 23 September 2026

Published: 1 October 2026

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1. Introduction

Guided by the dual carbon goal strategy, the installed capacity of wind power, photovoltaic and other renewable energy in China continues to rise, and the power system with high proportion of renewable energy has become an inevitable trend of power grid development. The increasing penetration of renewable energy introduces stronger uncertainty and short-term fluctuations into power-system operation, which increases the difficulty of reserve sizing and frequency-regulation scheduling [1,2]. Renewable energy stations and wind farms can provide frequency-regulation services, but their available regulation capability is strongly affected by renewable-power uncertainty, operating conditions and reserve margins [3,4]. However, renewable energy has significant anti-peaking characteristics and strong stochastic fluctuation characteristics. After large-scale integration, it has broken the traditional dispatching and operation mode of power systems, bringing unprecedented

pressure to the peak regulation and frequency regulation links of power grids [5,6]. As the core link of power system operation decision-making, electricity market clearing is the key carrier to realize the optimal allocation of peak and frequency regulation resources and the safe and economic operation of power grids [7,8].

Peak and frequency regulation capacity is the core physical boundary of the joint clearing model of energy and frequency regulation markets, and its quantification accuracy directly determines the collaborative allocation efficiency of thermal power deep peak regulation resources and frequency regulation resources. At present, the industry still mainly adopts the empirical value method and fixed coefficient method, that is, setting the frequency regulation capacity demand according to the operation experience of dispatchers or 5–8% of the system load prediction value. This method is simple in calculation but fails to consider the coupling effect of multi-dimensional influences such as renewable energy output fluctuation, load characteristic changes and meteorological factors, which easily leads to over-configuration or under-configuration of frequency regulation capacity. Early statistical studies on frequency regulation capacity demand quantification in academia mainly focused on two ideas: prediction error distribution and system historical frequency performance indicators [9,10]. The method based on prediction error distribution quantifies the frequency regulation capacity demand by statistically analyzing or probabilistically predicting the historical prediction errors of renewable energy and load to obtain the error distribution characteristics [11,12]. The method based on frequency performance indicators reversely deduces the frequency regulation capacity demand that meets the frequency quality requirements by analyzing the operation data such as system historical frequency deviation and ACE indicators [13,14]. The above traditional statistical methods have realized the preliminary transformation of frequency regulation capacity demand from “empirical” to “quantitative”, but there are obvious limitations: they fail to consider the comprehensive impact of continuous volatility and stochastic uncertainty of renewable energy output on frequency regulation capacity demand, only consider the power deviation at the dispatching time point, and ignore the continuous fluctuation characteristics of source-load within the time period [15].

To account for the continuous fluctuation characteristics of source-load within the time period, existing studies have proposed data-driven frequency regulation capacity demand quantification methods [16]. By constructing a data set with multi-dimensional features such as renewable energy, load, meteorology and frequency performance indicators, a data-driven mapping relationship is established to realize the prediction and quantification of frequency regulation capacity demand [17]. For example, the literature constructs a multiple linear regression model based on system historical frequency performance indicators to realize real-time quantification of frequency regulation capacity demand [18]. The difference from the aforementioned traditional statistical methods is that the former finds the statistical laws of frequency performance indicators (such as Area Control Error (ACE) and frequency deviation) through statistical analysis of a large number of historical operation data, thereby reversely calculating the frequency regulation capacity sufficient to cover these fluctuations, while the latter uses machine learning and other algorithms to “learn” the nonlinear relationship between complex factors affecting frequency regulation capacity demand (such as load, renewable energy output, meteorological conditions) and the final demand from historical data, so as to predict the future demand. The literature constructs an ensemble learning data-driven model combined with a chance-constraint error compensation method based on the prediction uncertainty of net load and renewable energy output, to realize the determination of regulation reserve capacity demand and its cost fair allocation [19,20]. However, the existing data-driven methods still have a core problem: in addition to frequency regulation capacity demand, system frequency control

performance indicators are also affected by other factors such as AGC control strategies and regulation performance of generating units participating in frequency regulation. Therefore, it is difficult to obtain the ideal frequency regulation capacity demand from the target frequency control performance.

This paper proposes a deviation-based method for quantifying frequency regulation capacity demand. The method defines upward and downward demand from maximum one-minute net-load deviations within each clearing interval. An improved weighted Euclidean distance supports the screening of historical samples and input features. A deep neural network (DNN) provides deterministic predictions, and adaptive-bandwidth kernel density estimation (ABKDE) supports prediction-error compensation. The main contributions are as follows:

1. An intra-interval target for regulation capacity demand. Upward and downward demand are defined separately using the maximum deviations between realized one-minute net load and the corresponding day-ahead forecast within each clearing interval. This definition represents the imbalance to be accommodated without deriving demand solely from observed frequency-control performance.
2. Joint screening of training samples and input features. A category-aware weighted Euclidean distance is used to identify historical samples relevant to the forecast day. Feature screening further selects inputs according to their matching characteristics, addressing heterogeneous feature groups and redundant information within the prediction framework.
3. Integration of deterministic prediction and uncertainty compensation. DNN prediction is combined with ABKDE-based error compensation to construct prediction intervals. Their upper bounds provide regulation capacity estimates that account for prediction uncertainty, with coverage and interval width evaluated jointly.

2. Sample Construction and Screening for Frequency Regulation Capacity Demand Quantification

2.1. Feature Construction of Frequency Regulation Capacity Demand Quantification Model

In power system operation, reasonable reservation of frequency regulation capacity is a key link to ensure frequency stability and cope with net load prediction deviation and real-time fluctuation. Renewable-energy resources can also provide dynamic frequency support through fast active-power regulation, although their available regulation capability depends on operating conditions and the reserved power margin [21]. The quantification of frequency regulation capacity demand needs to take into account both the uncertainty of net load itself (reflected by prediction error) and the occupation of regulation margin by minute-level short-term fluctuations within the time period. To accurately characterize this demand, this section defines the ideal upward and downward frequency-regulation capacity demands as the model output targets. For each clearing interval, the realized one-minute net-load trajectory is compared with the corresponding day-ahead net-load forecast. The upward regulation-capacity demand is defined as the maximum positive deviation of the realized net load from the forecast, whereas the downward regulation-capacity demand is defined as the maximum negative deviation in the opposite direction. These two quantities are evaluated independently because upward and downward regulation correspond to different system imbalance directions.

This definition is based on the operational requirement that the reserved regulation capacity should be sufficient to accommodate the largest net-load deviation occurring within the entire clearing interval. Compared with evaluating the deviation only at the dispatching instant, the maximum one-minute deviation accounts for continuous intra-interval fluctuations and therefore provides a more conservative system-level boundary for

reserve sizing. The target represents the capacity required under an idealized assumption that the required regulation response can be delivered within the clearing interval.

The resulting target is an idealized regulation-capacity boundary rather than a complete representation of actual automatic generation control deployment. It does not explicitly include generator ramp-rate limits, response delays, participation factors, transmission constraints, reserve offers or market-clearing decisions. Its engineering applicability is therefore to provide a data-driven capacity boundary for subsequent reserve allocation and joint energy–regulation market clearing. The downstream operational model must further verify deliverability and economic feasibility. Figure 1 shows the schematic diagram of the ideal upward and downward frequency-regulation capacity demands within a single clearing interval.

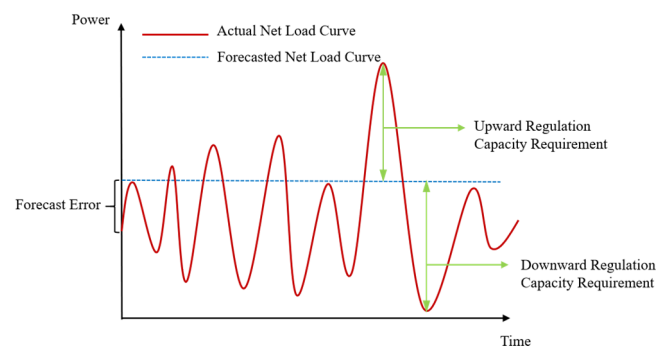


Figure 1. Schematic diagram of ideal system regulation-up and regulation-down capacity requirements.

In terms of input feature construction, this paper extracts the statistical features of net load and its related components from two dimensions of volatility and uncertainty: for each clearing period of the day before the prediction day, the maximum, minimum, mean and median of load power, renewable energy power and net load power are collected, respectively, to characterize the distribution range and central tendency of each power component. At the same time, the statistical values (maximum, minimum, mean and median) of positive and negative deviations of net load power relative to the power value at the start of the period are introduced to further reflect the power fluctuation situation in the clearing period. The above features together constitute the model input to fully express the correlation between source-load stochastic fluctuation and frequency regulation capacity demand. Meanwhile, considering that meteorological conditions are the core variables affecting the stochastic characteristics of load and renewable energy output, the predicted meteorological data (temperature, humidity, wind speed, etc.) for each period on the operation day are included in the input vector.

For the prediction day, the input features are restricted to information available before the day-ahead clearing stage, including calendar variables, historical load and renewable-generation data, and day-ahead meteorological forecasts. The realized net-load trajectory and realized weather conditions of the prediction day are not used as model inputs or for sample or feature screening.

To ensure the practicability of the proposed method in the day-ahead dispatching link, the net load data of the day before the operation day are used to construct the input vector, reserving sufficient time for the subsequent day-ahead clearing. The true value of the ideal system frequency regulation capacity demand in historical samples is calculated based on the actual 1-min net load curve and day-ahead prediction curve of historical operation days, in which the up and down frequency regulation capacity demands are quantified independently to reflect the regulation margin of the system in

different fluctuation directions. The constructed input and output feature sets are shown in Table 1.

Table 1. Feature construction for the frequency regulation capacity demand quantification model.

	Dimension	Description
Input	1–384	Extreme values, mean and median of renewable energy power in each clearing period of the day before the prediction day
	385–768	Extreme values, mean and median of load power in each clearing period of the day before the prediction day
	769–1152	Extreme values, mean and median of net load power in each clearing period of the day before the prediction day
	1153–1536	Extreme values, mean and median of positive/negative deviations of net load power relative to the power value at the start of each clearing period of the day before the prediction day
	1537	Holiday type of the prediction day
	1538–1825	Extreme values and mean of wind speed in each clearing period of the prediction day
	1826–2112	Extreme values and mean of temperature in each clearing period of the prediction day
	2113–2400	Extreme values and mean of humidity in each clearing period of the prediction day
Output	2401–2688	Extreme values and mean of rainfall in each clearing period of the prediction day
	1–96	Up and down frequency regulation capacity demand in each clearing period of the prediction day

It should be noted that Table 1 defines the feature vector structure of a single-day sample. In actual model training, the above feature vectors for consecutive multiple days (such as 10 days or 60 days) before the prediction day are selected to form the training set, as detailed in the case setting in Section 3.1.

2.2. Training Sample Construction and Screening Based on Feature Matching Degree

The accuracy of frequency regulation capacity demand prediction depends not only on the structural design of the model itself, but also on the representativeness of training samples and the effectiveness of input features. Considering the strong uncertainty of renewable generation, data-driven methods have been increasingly adopted to extract uncertainty characteristics and improve reserve requirement estimation [22]. In data-driven power system prediction tasks, if the feature distribution of training samples is significantly different from that of the scenario to be predicted, or the input features contain a large amount of redundant and irrelevant information, the generalization ability and prediction accuracy of the model will be significantly reduced, and even overfitting will occur. For this reason, this section proposes a dual screening strategy based on feature matching degree. Firstly, training samples highly similar to the scenario of the day to be predicted are screened from massive historical data, and then the most discriminative input features are further extracted from the high-dimensional feature set to lay a high-quality data foundation for the subsequent frequency regulation capacity prediction model.

2.2.1. Training Sample Screening Based on Improved Weighted Euclidean Distance

Traditional Euclidean distance is a common method to measure sample similarity, but it has obvious defects when processing multi-dimensional and heterogeneous feature data. Since the dimensions of continuous features such as renewable energy output, load fluctuation and meteorological factors are much higher than discrete features such as holiday type, the calculation results of traditional Euclidean distance will be seriously biased towards high-dimensional features, leading to the neglect of low-dimensional but important discrete features (such as holiday features), which cannot accurately reflect the true similarity between samples. To solve this dimension imbalance, this section proposes

an improved weighted Euclidean distance method by feature categories, and the calculation process is shown in Equations (1) and (2).

$$d_l^{q/n/r} = \sqrt{z_1|a_1 - b_1|^2 + \dots + z_w|a_w - b_w|^2} \quad (1)$$

$$d_l = \frac{1}{16} \sum_{q=1}^{16} d_l^q + \frac{1}{12} \sum_{q=1}^{12} d_l^n + d_l^r \quad (2)$$

where $d_l^{q/n/r}$ is the weighted Euclidean distance of features; z is the weight of the k -th dimension feature (obtained by the Pearson correlation coefficient), and the subscript k is the data dimension number; a and b are two w -dimensional sample data; q represents the fluctuation characteristics of load, renewable energy output and net load on the day before the prediction day; n represents the meteorological factor characteristics of the prediction day; r represents the holiday type corresponding to the prediction day; l represents the number of days; d_l is the final Euclidean distance calculation result of the two samples, which can be used to quantify the matching degree between samples.

This method first divides the input features into three categories and calculates the weighted Euclidean distance for each category of features, respectively. The weight of the k -th dimension feature is determined by the Pearson correlation coefficient, which can reflect the influence degree of different features on frequency regulation capacity demand. On this basis, the distances of various features are combined to obtain the final comprehensive Euclidean distance between two samples, which is used to quantify the matching degree between samples. After calculating the comprehensive Euclidean distance between all historical samples and the prediction day sample, the L samples with the smallest distance (i.e., the highest matching degree) are selected to form the final training sample. Before calculating the distance, continuous variables within each feature category are normalized to eliminate the influence of different measurement scales. The Pearson correlation coefficients are converted into nonnegative feature weights, and the weights are normalized within each feature category. This treatment prevents a feature category from dominating the distance calculation solely because it contains more variables or has a larger numerical scale. The category-specific distances are then aggregated to obtain the improved weighted Euclidean distance used for sample matching. The present section focuses on defining the proposed distance and its calculation procedure. A direct numerical comparison between the improved weighted Euclidean distance and the conventional Euclidean distance is beyond the scope of this method description and will be considered in future work.

For each prediction day, candidate training samples are selected only from historical days preceding the prediction day. The similarity calculation does not use the realized net load or realized meteorological conditions of the prediction day.

2.2.2. Input Feature Screening Based on Sample Weights

The initial input feature dimension of the frequency regulation capacity demand prediction model constructed in this paper is as high as 2688 dimensions, which inevitably contains a large number of redundant features and features weakly correlated with the prediction target. These invalid features will not only increase the computational complexity and training time of the model, but also introduce noise interference and reduce the prediction accuracy of the model. For this reason, on the basis of training sample screening, this section further proposes an input feature screening method based on sample weights to extract the feature subset that best reflects the change law of frequency regulation capacity demand.

The core idea of this method is: the higher the matching degree between the training sample and the prediction day sample, the greater the contribution of its features to the prediction result, so higher weights should be given in the feature matching degree calculation. Firstly, the weight of each sample is determined according to the normalized Euclidean distance between the training sample and the prediction day sample w_l , as shown in Equation (3). The smaller the distance between samples, the larger the corresponding weight, so that the features of high-matching samples play a leading role in the screening process. On this basis, the Euclidean distance between each input feature in the training samples and the prediction day sample is calculated dimension by dimension, and the sample weight is used for weighted averaging to obtain the matching degree of the p -th dimension feature d^p , as shown in Equation (4):

$$w_l = 1 - \frac{d_l - d_l^{\min}}{d_l^{\max} - d_l^{\min}} \quad (3)$$

$$d^p = \frac{1}{L} \sum_{l=1}^L w_l d_l^p \quad (4)$$

where $d_l^{\max}$ and $d_l^{\min}$ represent the maximum and minimum Euclidean distances of the screened training samples, respectively; d_l^p represents the Euclidean distance between different input features in the l -th sample and the prediction day. The higher the matching degree score, the better the consistency of the feature between the training samples and the prediction day sample, and the greater the value for predicting frequency regulation capacity demand. Finally, the T features with the highest matching degree scores are selected as the final input of the model, and the input feature dimensions of both training samples and samples to be predicted are reduced to T dimensions.

3. Frequency Regulation Demand Quantification and Error Compensation Method Based on Deep Neural Network

3.1. Deterministic Prediction Model of Frequency Regulation Capacity Based on DNN

This section uses DNN to establish a deterministic prediction model of frequency regulation capacity demand. Recently, data-driven forecasting methods based on deep learning and probabilistic prediction have been widely applied to reserve requirement estimation, providing an effective way to characterize nonlinear relationships between renewable uncertainty and regulation demand [23,24]. It should be pointed out that the core of this section is not to discuss which data-driven model to choose to construct the deterministic prediction model, and other data-driven methods can also be used to quantify frequency regulation capacity demand. The output value of each neuron in DNN is the weighted sum of its inputs, which is nonlinearly transformed by the activation function. The data transfer formula between layers is shown in Equation (5):

$$x_j^{(l)} = f\left(\sum_{i=1}^n W_{ij}^{(l)} x_i^{(l-1)} + b_j^{(l)}\right) \quad (5)$$

where $x_j^{(l)}$ is the output of the j -th neuron in the l -th layer; n is the total number of layers of DNN; $W_{ij}^{(l)}$ is the weight matrix between the i -th neuron in the $l-1$ -th layer and the j -th neuron in the l -th layer; $b_j^{(l)}$ is the bias term of the j -th neuron in the l -th layer. The n -th layer is the final output $\hat{y}$ of DNN, as shown in Equation (6):

$$\hat{y} = x_j^{(n)} = \sum_{i=1}^n W_{ij}^{(n)} x_i^{(n-1)} + b_j^{(n)} \quad (6)$$

The hidden layer adopts Leaky ReLU (LReLU) as the activation function. Compared with the traditional ReLU activation function, LReLU can output a non-zero gradient when the input is negative, which can significantly improve the training stability and convergence speed of the model. The function expression of LReLU is shown in Equation (7):

$$f(x) = \max(0.01x, x) \quad (7)$$

Considering that this model aims to predict the frequency regulation capacity demand in 96 clearing periods in the future, it is a typical multi-output regression prediction task. Therefore, the output layer of the DNN model adopts a linear activation function. This design not only retains the feedforward calculation accuracy of neurons, but also effectively avoids the problems of gradient disappearance or limited mapping range that may be caused by nonlinear activation functions in regression tasks. Its mathematical expression is shown in Equation (8):

$$f(x) = x \quad (8)$$

The DNN is trained by the screened sample data pairs. This paper adopts Mean Squared Error (*MSE*) as the loss function and continuously adjusts the parameters to minimize the loss function *MSE*, as shown in Equation (9):

$$MSE = \frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2 \quad (9)$$

where $\hat{y}_i$ is the predicted value of frequency regulation capacity obtained by the DNN model; y_i is the true value of frequency regulation capacity; N is the number of samples. The training algorithm adopted in this section combines the Root Mean Square Propagation algorithm with a learning rate decay strategy, which realizes the adaptive adjustment of each parameter update step size, thereby improving the speed of parameter convergence. Meanwhile, as the training process progresses, the strategy of gradually reducing the learning rate helps to reduce the oscillation effect of the algorithm.

$$d\theta^{(k)} = \nabla_{\theta^{(k-1)}} L \quad (10)$$

$$r^{(k)} = \rho r^{(k-1)} + (1 - \rho) d\theta^{(k)} \odot d\theta^{(k)} \quad (11)$$

$$\Delta\theta^{(k)} = \frac{\alpha^{(k)}}{\sqrt{\delta + r^{(k)}}} \odot d\theta^{(k)} \quad (12)$$

$$\theta^{(k)} = \theta^{(k-1)} - \Delta\theta^{(k)} \quad (13)$$

$$\alpha^{(k)} = \begin{cases} \varepsilon^{k-1} \alpha_0 & \text{if } \varepsilon^{k-1} \alpha_0 > 0.00001 \\ 0.00001 & \text{if } \varepsilon^{k-1} \alpha_0 < 0.00001 \end{cases} \quad (14)$$

where $d\theta^{(k)}$ is the gradient of the loss function with respect to the parameter θ at the k -th iteration; $r^{(k)}$ is the moving average of the squared gradient of the parameter at the k -th update; $\Delta\theta^{(k)}$ is the parameter update amount at the k -th step; $\alpha^{(k)}$ is the learning rate at the k -th update. After training, DNN can be used to predict the specific value of the maximum fluctuation of frequency regulation capacity demand in each clearing period of the operation day.

The proposed deep neural network comprises three hidden layers with 256, 128, and 64 neurons, respectively. All hidden layers employ the Leaky ReLU activation function, whereas the output layer adopts a linear activation function. The ABKDE module is applied to the residuals between the DNN predictions and the corresponding target values obtained from the development data. A kernel function K is used to estimate the residual probability

density. First, a global baseline bandwidth is determined, and the bandwidth for each residual sample is then adaptively adjusted according to the local density of the residual distribution. The global bandwidth and the adaptive adjustment parameter are defined in Equations (16) and (17). The nominal confidence level used for interval prediction is 95%. Accordingly, the lower and upper limits of the two-sided prediction interval are obtained from the 0.025 and 0.975 residual quantiles, respectively. The upper interval limit is used as the regulation-capacity boundary. The realized residuals of the evaluated prediction period are not used to fit the ABKDE model or to construct the prediction interval. PICP and PINAW are then used to evaluate the coverage reliability and normalized interval width of the resulting prediction interval.

3.2. Prediction Error Compensation Method Based on ABKDE

Data-driven models inevitably have fitting deviations. If the predicted frequency regulation capacity is less than the actual demand in the clearing period, it will lead to insufficient regulation margin reserved by the system, thereby reducing the frequency control performance. For this reason, this section introduces an error compensation mechanism based on Adaptive Bandwidth Kernel Density Estimation (ABKDE) to obtain the confidence interval of frequency regulation capacity demand through interval prediction, and selects the upper limit of the interval as the final reserved frequency regulation capacity of the system. This upper limit corresponds to the maximum possible frequency regulation capacity demand under a given confidence level, which can fundamentally avoid the safety risk that the predicted value is lower than the actual value. The deterministic prediction results output by the DNN are input into the ABKDE model for interval prediction, and the specific implementation steps are as follows. In this study, the nominal confidence level for interval prediction is set to 95%. Accordingly, the lower and upper limits of the two-sided prediction interval are determined using the 0.025 and 0.975 quantiles of the estimated residual distribution, respectively. The upper endpoint is used as the regulation-capacity boundary. The residual distribution is estimated from the available development data, and the realized residuals of the prediction period are not used to construct the interval. The bandwidth is selected according to the adaptive-bandwidth kernel density estimation procedure described below. PICP is used to measure the proportion of realized observations covered by the prediction interval, whereas PINAW measures the normalized interval width. These two metrics are interpreted jointly because improved coverage may be accompanied by an increase in interval width.

Kernel Density Estimation (KDE) is a non-parametric probability density estimation technique that does not require pre-assuming the data distribution form. Its core idea is to superimpose a smooth kernel function on each observation sample point, and characterize the probability distribution characteristics of the data in the entire feature space through the weighted sum of kernel functions. The specific calculation process is shown in Equation (15):

$$f(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right) \quad (15)$$

where K represents the selected kernel function; n is the total number of samples participating in the estimation; x_i is the prediction sample point output by DNN; h is the bandwidth parameter controlling the smoothness.

Although the traditional KDE method can realize the preliminary estimation of data probability density, it adopts a globally unified fixed bandwidth parameter. When the data presents a non-uniform distribution with large local density differences, two typical problems are prone to occur: in data-intensive areas, excessive bandwidth may lead to over-smoothing of local details of the distribution; while in data-sparse areas, too small

a bandwidth will introduce too much noise and cause overfitting. To solve this inherent defect, ABKDE is proposed, whose core improvement is to adopt a bandwidth parameter that dynamically changes with the local density of data instead of a globally unified value. Specifically, in areas with sparse sample distribution, the bandwidth is increased to reduce the variance of the estimation result and improve the overall smoothness; while in areas with dense sample distribution, the bandwidth is reduced to reduce the estimation deviation and retain the local detail characteristics of the data distribution. The specific mathematical formulas of the ABKDE method are shown in Equations (16) and (17):

$$h_i(x) = h_0 \left(\frac{\lambda}{g(x)} \right)^{\frac{1}{2}} \quad (16)$$

$$f(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{h_i} K \left(\frac{x - x_i}{h_i} \right) \quad (17)$$

where h_0 is the global baseline bandwidth, which serves as the benchmark reference value for local bandwidth adjustment of all sample points; λ is the bandwidth adjustment parameter, which is used to adjust the response amplitude of the bandwidth to the change of local data density; $g(x)$ represents the preliminary density estimation result calculated based on the initial global bandwidth at sample point x , which $f(x)$ is the probability density function.

To ensure that the predicted value is moderately higher than the true result of the actual clearing point, this section further introduces the Cumulative Distribution Function (CDF) and Percent Point Function (PPF). CDF is used to measure the probability that the random variable X takes a value not exceeding a given value x , and its expression is shown in Equation (18):

$$F(x) = \int_{-\infty}^x f(x) dx \quad (18)$$

This function has a non-decreasing characteristic, and the output range is between 0 and 1. Furthermore, the inverse function of the CDF can be obtained to get the PPF, as shown in Equation (19):

$$x = F^{-1}(p) \quad (19)$$

where p is usually between 0 and 1. If the confidence level is selected as 95%, then p takes 0.975, and at this time x represents the predicted value corresponding to this confidence level.

Based on this, the boundary quantification of frequency regulation capacity demand is realized. Although frequency regulation capacity solves the problem of deviation between the final intraday decision plan and the actual net load curve in the real-time operation stage, the system still faces the problem that the deviation between the intraday net load prediction curve and the day-ahead decision plan cannot be considered. For this reason, the subsequent chapter will further discuss the boundary quantification of peak regulation capacity demand to construct a complete regulation resource allocation system.

4. Case Study

4.1. Introduction to Simulation Data and Comparison Methods

To verify the actual effect of the proposed deterministic frequency regulation capacity demand prediction model and error compensation strategy, this section selects the actual one-year operation data of a provincial power grid in 2023 (including historical frequency regulation capacity and meteorological elements, etc.) for verification. The complete data set was divided chronologically into training and test sets at a ratio of 8:2. The earlier 80% of the observations were used for model training, sample screening and feature

screening, while the remaining 20% were reserved for independent testing. The data were not randomly shuffled because the chronological order had to be preserved for the day-ahead forecasting task. The realized target values and realized meteorological variables in the test period were not used during model training, sample screening, feature screening or model construction. They were accessed only after the predictions had been generated to calculate the evaluation metrics. The renewable energy penetration rate is 14.69%, and the load prediction adopts a sliding window mechanism: an independent load prediction model is trained for each prediction day, and the number of training samples remains constant. It should be pointed out that the actual meteorological data cannot be obtained when predicting the frequency regulation capacity demand on the operation day. Therefore, it is assumed that the meteorological prediction error obeys a zero-mean Gaussian distribution to generate predicted meteorological data, with an average accuracy of 90%. The test dataset contains different operating conditions in different seasons and dates. The spring scenario is used to evaluate the overall prediction performance of the proposed model under representative seasonal conditions. In addition, several specific test cases are selected from the test dataset to further analyze the model performance under different daily operating conditions. Due to the variations in renewable energy output, load fluctuations, and meteorological factors, the evaluation metrics may vary among different test cases.

- M1: Data-driven prediction model based on a Deep Neural Network (DNN), using improved Euclidean distance to screen training samples and input features, selecting 60 samples with the highest similarity to the input of the prediction day to form the training set;
- M2: DNN model with input feature screening but no training sample screening, directly using all data of 60 days before the prediction day for training;
- M3: DNN model with training sample screening but no input feature screening, directly using 60 samples most similar to the prediction day for training;
- M4: DNN model with neither training sample screening nor input feature screening, directly using the data of 60 days before the prediction day as the training set;
- M5: Adding ABKDE on the basis of M1;
- M6: Adding ABKDE on the basis of M4;
- M7: DNN model based on M1, but using conventional Euclidean distance instead of improved weighted Euclidean distance to screen training samples.

The specific descriptions of comparison methods M1–M6 are shown in Table 2.

Table 2. Comparison methods and purposes.

Comparison Method	Comparison Purpose
M1, M2	Verify the effectiveness of the proposed training sample screening method
M1, M3	Verify the effectiveness of the input feature screening method
M1, M4	Verify the effectiveness of collaborative screening of samples and features
M5, M6	Verify the ability of the interval prediction model to ensure the safety of regulation margin
M1, M7	Verify the effectiveness of the improved weighted Euclidean distance for training sample screening

For the deterministic prediction model, this section selects four core indicators for accuracy evaluation: Coefficient of Determination (R^2), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The closer the coefficient of determination is to 1, the stronger the model's ability to explain the data. The smaller the values of the other three error indicators, the higher the prediction accuracy of the model. Moreover, RMSE imposes a more severe penalty on larger prediction errors

and can better reflect the overall error level of the model. For the interval prediction model, two indicators, Prediction Interval Coverage Probability (PICP) and Prediction Interval Normalized Average Width (PINAW), are used to comprehensively evaluate its performance. The higher the PICP, the greater the probability that the actual value falls within the prediction interval and the stronger the prediction reliability. The smaller the PINAW, the more accurate the prediction result. The two together balance the reliability and accuracy requirements of interval prediction.

4.2. Validation of Frequency Regulation Capacity Demand Quantification Effectiveness

4.2.1. Comparison of Frequency Regulation Capacity Demand Prediction Accuracy

This section first conducts simulation verification on the data-driven quantification method of frequency regulation capacity demand. The training sample set is constructed based on the continuous historical operation data in spring 2023 (from February 1 to April 29), and the feature data of the corresponding period are selected to construct the model input features. Table 3 shows the comparison results of various deterministic prediction indicators of methods M1–M4 in spring scenarios.

Table 3. Deterministic forecasting metrics of different comparison methods.

Evaluation Criterion	M1	M2	M3	M4	M7
R^2 / %	98.31	94.1	94.74	93.6	95.1
MAE/MW	5.03	6.72	5.87	7.8	6.24
RMSE/MW	5.44	7.93	7.23	10.14	6.84
MAPE / %	3.62	6.45	5.85	8.08	4.97

It can be seen from Table 3 that compared with M2–M4, M1 has a frequency regulation capacity average coefficient of determination R^2 closer to 1, and lower values of MAE, RMSE and MAPE. It can be seen that the M1 model has stronger nonlinear fitting ability and prediction accuracy. In addition, comparing M1 and M3, under the same sample conditions, the MAPE is reduced by 38.12% (from 5.85% to 3.62%) after introducing input feature screening. This result fully verifies the effectiveness of the input feature screening technology proposed in this paper. Similarly, we further compared methods M2 and M4. After screening similar samples using improved Euclidean distance, the MAPE decreased from 8.08% to 6.45%, a decrease of 20.17%, verifying the effectiveness of the training sample screening technology. The comparisons in Table 3 are designed as controlled ablation experiments to isolate the effects of input-feature screening and training-sample screening within the proposed DNN framework. Random Forest, XGBoost and LSTM would provide useful external benchmarks for evaluating the prediction performance of different model families. However, these models were not included in the present experimental comparison. Therefore, the results reported in this section are interpreted as evidence for the effectiveness of the proposed screening strategies under the tested DNN configuration, rather than as proof of universal superiority over conventional machine-learning or other deep-learning models. A systematic benchmark comparison using the same input information, chronological data partition, preprocessing procedure and evaluation metrics will be considered in future work.

The above analysis shows that the proposed method helps to improve the fitting effect, accuracy and stability of the model. To compare the accuracy differences of each method in frequency regulation capacity demand prediction, Figure 2 plots the comparison between the predicted values and actual values of methods M1 to M4.

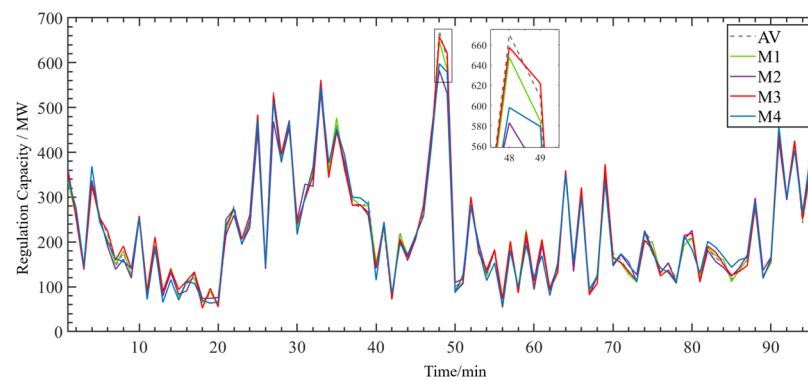


Figure 2. Comparison between predicted and actual values of frequency regulation capacity for M1–M4.

Furthermore, M7 is introduced to further verify the effectiveness of the improved weighted Euclidean distance. Compared with M1, M7 adopts the conventional Euclidean distance for training sample screening while keeping the other components unchanged. As shown in Table 3, M7 achieves an R^2 of 95.10% and a MAPE of 4.97%, which are inferior to those of M1. This indicates that the conventional Euclidean distance cannot fully characterize the similarity between historical samples and the prediction scenario due to the heterogeneous characteristics and different importance levels of input features. By introducing feature weights and considering the differences among feature categories, the improved weighted Euclidean distance can select more representative training samples, thereby improving the prediction accuracy of frequency regulation capacity demand.

It can be clearly seen from Figure 2 that the prediction curve of M1 proposed in this paper has the best fitting degree with the actual operation curve, and the prediction accuracy is the best. The fitting effect of method M3 is the second, and the overall trend is close to the true value. In contrast, the prediction curve of method M4 has the most significant deviation from the actual value, and the overall prediction effect is relatively poor. Therefore, it is proved that the data-driven quantification method of frequency regulation capacity demand proposed in this chapter is effective for frequency regulation capacity prediction.

4.2.2. Comparison of Frequency Regulation Capacity Prediction Security

To verify the ability of the interval prediction model to ensure the system regulation margin, the results of Prediction Interval Normalized Average Width (PINAW) and Prediction Interval Coverage Probability (PICP) of methods M5 and M6 are compared, as shown in Table 4.

Table 4. Comparison of prediction indicators between methods M5 and M6.

Evaluation Criterion	M5	M6
PINAW/%	7.46	10.78
PICP/%	100	86.81

It can be seen from Table 4 that method M5 still achieves 100% PICP under the premise that PINAW is smaller than M6, indicating that this method can achieve full coverage of real net load fluctuations under a narrower prediction interval, and the upper boundary of the prediction can reliably envelope the actual value. The above results show that the deterministic prediction accuracy has a significant impact on the performance of the interval prediction model: the higher the deterministic prediction accuracy, the

more compact and reliable the obtained interval prediction, and the corresponding system frequency regulation capacity demand is closer to the actual operation scenario.

To intuitively compare the differences in the impact of different methods on system frequency regulation capacity configuration, Figure 3 shows the frequency regulation capacity reservation at the 10th clearing point on 31 May 2023.

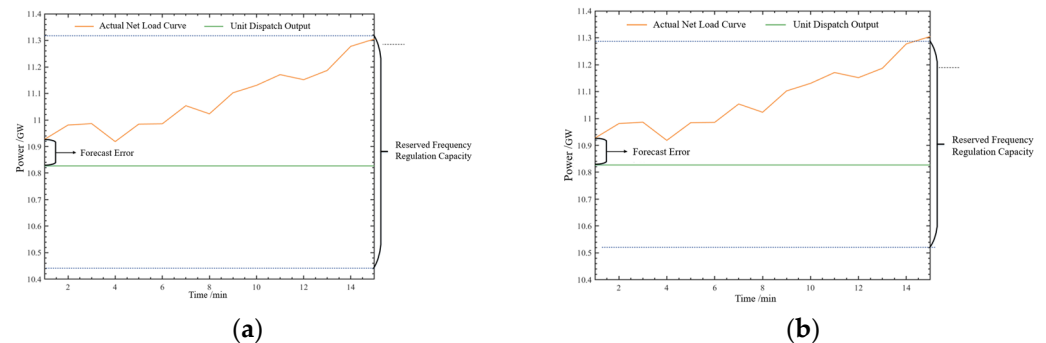


Figure 3. Comparison of reservation conditions between methods M5 and M6 at the 10th time instant: (a) Frequency regulation capacity reservation in Case M5; (b) Frequency regulation capacity reservation in Case M6.

It can be seen from Figure 3 that at the 10th clearing moment, the frequency regulation capacity allocated by M6 is difficult to adapt to the fluctuation characteristics of the actual net load, resulting in the system's frequency regulation performance failing to meet the operation standard at this time point. In contrast, the frequency regulation capacity reserved by M5 is more sufficient, which can meet the frequency regulation demand and ensure the safe operation of the power grid and frequency stability. This result further confirms the guarantee effect of the interval prediction model on the system regulation margin.

From a market-operation perspective, the predicted upper boundary can be provided as an input to a subsequent reserve-allocation or joint energy–frequency-regulation market-clearing model. An underestimated boundary may increase the risk of insufficient reserve, whereas an overly conservative boundary may lead to redundant reserve capacity and higher reserve-procurement or opportunity costs. The PICP and PINAW metrics used in this study describe empirical interval coverage and relative interval width, respectively, but they do not directly quantify reserve-allocation benefits or operating-cost savings. A quantitative evaluation of these practical effects would require additional information on generator offers, ramping limits, reserve deliverability, network constraints and market-settlement rules, together with a dedicated market-simulation model. These aspects are therefore identified as directions for future work.

4.2.3. Scalability Validation

To verify the scalability of the proposed method, this section further tests the prediction accuracy of the proposed method under different renewable energy penetration rates and different seasons.

(1) Different Renewable Energy Penetration Rates

In the aforementioned simulation link, the sample data source corresponds to a renewable energy penetration rate of 14.69%. To test the scalability of the proposed method under different penetration rates, this section further constructs test scenarios with penetration rates of 25% and 35%, respectively. The short-term variability of renewable generation is an important factor in backup-capacity planning because increasing variability may change the amount of regulating capacity required by the system [22]. Therefore, the adaptability of the proposed method is further examined under different renewable-energy penetration levels. The specific implementation method is to superimpose the historical

data of renewable energy output on the actual net load of the original provincial power grid. The 14.69% penetration level represents the measured baseline of the original data set, whereas the 25% and 35% penetration levels are constructed as controlled stress-test scenarios. The same chronological operating sequence is retained to provide a common basis for comparison. However, this construction is not intended to reproduce all physical and operational changes associated with a future high-renewable-energy power system. In particular, it does not explicitly represent changes in installed capacity, geographical diversity, renewable curtailment, forecasting accuracy, network congestion, or the correlation between load and renewable output. Therefore, the results are interpreted as a sensitivity analysis of the proposed method under increased renewable-output variability, rather than as a calibrated prediction of the performance of a future power grid. The test results under different penetration levels are shown in Table 5.

Table 5. Comparison of forecasting metrics under different renewable energy penetration levels.

Renewable Energy Penetration Rate	Evaluation Criterion	M1	M2	M3	M4
25%	R^2 / %	97.84	93.75	94.39	93.16
25%	MAE / MW	5.16	6.84	6.05	7.95
25%	RMSE / MW	5.55	8.11	7.39	10.3
25%	MAPE / %	3.78	6.59	5.97	8.26
35%	R^2 / %	97.03	93.23	93.35	92.79
35%	MAE / MW	5.56	7.11	6.42	8.32
35%	RMSE / MW	5.81	8.33	7.74	10.55
35%	MAPE / %	4.17	6.86	6.35	8.64

As shown in Table 5, with the increase in renewable energy penetration rate, the stochastic volatility of power grid net load increases significantly, leading to different degrees of attenuation in the accuracy indicators of each prediction model. However, benefiting from the screening of sample data and input features, when the renewable energy penetration rate increases to 35%, the MAPE value of M1 is only 4.17%, which is significantly better than M2, M3 and M4. Moreover, when the penetration rate increases by 10%, the MAPE of M1 only increases by 0.39%, while the MAPE of method M4 increases by 0.38%, but its MAPE base is as high as 8.64%. The longitudinal comparison shows that the error growth trend of M1 is gentler in high volatility environments. The above results show that the proposed method can maintain high prediction accuracy under different renewable energy penetration rates. To further verify the adaptability of the interval prediction model to different penetration scenarios, Table 6 lists the test results of methods M5 and M6.

Table 6. Comparison of indicators for methods M5 and M6 under different new energy penetration levels.

Renewable Energy Penetration Rate	Evaluation Indicator	M5	M6
25%	PINAW / %	8.78	14.64
25%	PICP / %	100	84.79
35%	PINAW / %	9.45	18.67
35%	PICP / %	100	79.52

The above results show that the proposed method M5 can achieve full coverage of the real frequency regulation capacity demand under a more compact prediction interval, which not only avoids the redundant configuration of frequency regulation capacity caused by too wide intervals, but also eliminates the lack of frequency regulation margin caused by insufficient interval coverage. Further analysis shows that the excellent performance

of method M5 stems from its high-precision deterministic prediction basis: the higher the deterministic prediction accuracy, the closer the center value of the interval prediction is to the true value, and thus the interval width can be greatly compressed on the premise of ensuring 100% coverage, making the finally configured frequency regulation capacity more in line with the actual operation demand of the system. However, method M6 is limited by insufficient deterministic prediction accuracy and needs to expand the interval width to barely improve the coverage rate, but still cannot achieve full coverage of the true value. Its performance attenuation is more obvious in high penetration scenarios, and it is difficult to meet the frequency regulation margin guarantee requirements of power systems with a high proportion of renewable energy.

(2) Different Seasons

This section will further verify the effectiveness of the proposed method based on different seasons, as shown in Tables 7 and 8.

Table 7. Comparison of performance indicators for M1–M4 across different seasons.

	Evaluation Criterion	M1	M2	M3	M4
Spring	R ² /%	97.03	93.23	93.35	92.79
	MAE/MW	5.56	7.11	6.42	8.32
	RMSE/MW	5.81	8.33	7.74	10.55
	MAPE/%	4.17	6.86	6.35	8.64
Summer	R ² /%	96.67	92.9	93.04	92.52
	MAE/MW	5.7	7.26	6.5	8.4
	RMSE/MW	5.9	8.45	7.87	10.62
	MAPE/%	4.25	6.92	6.43	8.78
Autumn	R ² /%	96.35	92.44	92.58	92.09
	MAE/MW	5.7	7.26	6.62	8.49
	RMSE/MW	5.96	8.52	7.92	10.65
	MAPE/%	4.27	6.99	6.48	8.78
Winter	R ² /%	96.12	92.5	92.52	92.04
	MAE/MW	5.85	7.38	6.77	8.63
	RMSE/MW	6.14	8.64	7.9	10.77
	MAPE/%	4.49	7.11	6.56	8.87

Table 8. Comparison of performance indicators for M5–M6 across different seasons.

Season	Evaluation Indicator	M5	M6
Spring	PINAW/%	7.46	10.78
Spring	PICP/%	100	86.81
Summer	PINAW/%	5.56	11.91
Summer	PICP/%	100	89.68
Autumn	PINAW/%	5.72	11.28
Autumn	PICP/%	100	88.79
Winter	PINAW/%	5.94	11.74
Winter	PICP/%	100	85.55

It can be seen from Table 7 that under different seasonal climate backgrounds, M1 shows comprehensive advantages in all seasons: in spring scenarios, the R² of M1 reaches 97.03%, and MAE, RMSE and MAPE are 5.56 MW, 5.81 MW and 4.17%, respectively; all indicators are significantly better than the comparison methods. In summer, autumn and winter scenarios, the R² of M1 is 96.67%, 96.35% and 96.12%, respectively, always maintaining a high fitting degree of more than 96%. The error indicators such as MAE, RMSE and MAPE are all the best, and MAPE only fluctuates slightly between 4.25% and

4.49%, which is lower than the error level of 6–9% of the comparison methods, verifying the strong adaptability of the proposed method to seasonal characteristic changes.

It can be seen from Table 8 that in different seasons, under the premise that the PICP indicator remains 100%, the average interval width obtained by method M5 is narrower than that of M6, which strongly indicates that method M5 can make the predicted value slightly higher than the actual value, and once again verifies the guarantee effect of the interval prediction model on the system regulation margin.

5. Conclusions

Aiming at the core problems that the peak and frequency regulation pressure of power systems increases sharply under the integration of a high proportion of renewable energy, and the traditional boundary quantification method of energy and frequency regulation market joint clearing is difficult to adapt to the stochastic fluctuation characteristics of renewable energy, this paper proposes a boundary determination method of joint clearing model based on deviation prediction. By constructing a multi-dimensional feature set to comprehensively characterize various factors affecting frequency regulation capacity demand, adopting improved weighted Euclidean distance to realize dual screening of training samples and input features, and combining DNN and ABKDE to realize accurate prediction and error compensation of frequency regulation capacity. Based on the case verification of actual operation data of a provincial power grid, the following conclusions are drawn:

1. The dual screening technology of training samples and input features based on improved weighted Euclidean distance can significantly improve the prediction accuracy of data-driven models. Among them, input feature screening reduces the prediction MAPE by 38.12%, training sample screening reduces the MAPE by 20.17%, and after collaborative adoption, the frequency regulation capacity prediction MAPE is reduced to 3.62%, and R^2 reaches 98.31%;
2. After introducing the ABKDE error compensation mechanism, 100% PICP can be achieved under the premise that PINAW is only 7.46%, which not only fully covers all actual net load fluctuation scenarios to ensure system safety, but also avoids resource waste caused by excessive reserved capacity;
3. The proposed method maintains excellent performance under different renewable energy penetration rates (15–35%) and four-season scenarios, and has good universality and engineering application value.

Author Contributions: Conceptualization, H.Z. (Haibing Zhang) and M.X.; methodology, H.Z. (Haibing Zhang), Y.Z. and M.X.; software, H.Z. (Haibing Zhang) and Y.Z.; validation, H.Z. (Hang Zhan), Q.R. and X.L.; formal analysis, H.Z. (Haibing Zhang) and Y.Z.; investigation, H.Z. (Hang Zhan), Q.R. and X.L.; resources, H.Z. (Hang Zhan) and H.X.; data curation, H.Z. (Hang Zhan) and Q.R.; writing—original draft preparation, H.Z. (Haibing Zhang); writing—review and editing, Y.Z. and M.X.; visualization, H.Z. (Haibing Zhang) and X.L.; supervision, M.X.; project administration, H.X. and M.X.; funding acquisition, M.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science and Technology Project of State Grid Chongqing Electric Power Company (522023260015).

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to confidentiality restrictions associated with power-grid operational data.

Conflicts of Interest: Authors Haibing Zhang, Hang Zhan, Qingyue Ran, Xiaoju Li and Hanlin Xia were employed by State Grid Chongqing Electric Power Research Institute. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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