Improvement of Renewable Power Forecasting Indicators Based on System Flexibility

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***Abstract*—The evaluation index of renewable power forecasting plays an important role in guiding the power grid dispatching department and the operation of renewable power plants. Most of the current evaluation indexes can hardly reflect the relationship between prediction error and system flexibility. Firstly, this paper studies the evaluation index of system flexibility, determines the weight of different flexibility indexes by entropy method, and quantifies the flexibility of power system. On the basis of the existing index, the system flexibility is introduced to improve the existing index, and a new error evaluation index Root Weighted Squared Error is obtained. The simulation results show that the new evaluation index has good performance in measuring the level of single station prediction and multi-station scheduling.**

Keywords—system flexibility, entropy method, weight matrices, root weighted square error

I. INTRODUCTION

Renewable energy power generation has the characteristics of large volatility and strong randomness [1]. Ultra-short-term forecasting model of photovoltaic power generation based on cloud movement and multi-index fusion wind power prediction model are applied to renewable energy power prediction. [2-6]. According to the predicted value of renewable energy generation in the past, the dispatcher makes the future conventional energy generation plan [7]. The large prediction error of renewable energy power will not be conducive to the operation of conventional energy units, and may affect the power system, affect the power quality of the load side, and bring trouble to the production and life of users [8-11].

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are commonly used evaluation indexes in renewable energy prediction. They can objectively reflect the error between the real value and the predicted value, but there are still some limitations [12-17]. In order to better evaluate the forecast performance, the Northwest Energy Regulatory Bureau of China's National Energy Administration issued the "Implementation Rules for Grid-Connected Operation of Power Plant in Northwest China", this rule will add Relative Harmonic Error (RHE) to the ultra-short-term power forecasting evaluation system [18]. Chen et al. also proposed Weight Root Mean Square Error (WRMSE) to measure the prediction performance of renewable energy stations [19].

At present, most indicators have the same error weight for each time point and period [20-23]. However, in the grid, the sensitivity of the system to error is different at different times. When the flexibility of the system is low, the accuracy of the error is higher. A small prediction error can also cause the power system to collapse [24].

In order to more accurately determine the forecast level of wind farms. Yao et al. determined load peak and trough periods according to load output curve, and calculated the maximum forward error of the system load peak and the maximum negative error of the load valley [25].

C. G. Min et al. proposed a method for quantifying power system flexibility using effective ramping capability (ERC) obtained from conventional power plants, which is based on payload capacity to determine the capacity of variable renewable energy sources [26]. ERC is characterized as the contribution capacity of conventional power plants to net load demand, which can be used to describe the contribution capacity of power plants to the system in the specified direction at different time scales. It is a function of the minimum and maximum output levels of the power plant and the maximum ramp rate.

E. Lannoye et al. proposed the insufficient ramping resource expectation (IRRE). IRRE refers to the expectation that the power system will be unable to cope with the net load change [27]. The computational structure of IRRE is similar to that of LOLE, but IRRE forms a flexible resource distribution available in each direction and time range. By calculating the IRRE of the selected period, the adaptability of the system to the change of net load in the current period can be understood [28].

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The sensitivity of the power system to the prediction error is different at different times. When the system flexibility is low, the prediction accuracy of the renewable energy station is required to be high. When the system flexibility is high, the prediction error can be tolerated to a certain extent. However, RMSE, MAE and other indicators cannot evaluate the forecast level of renewable energy stations according to the system flexibility. Power system flexibility can be measured by multiple indicators: (1) upward adjustable capacity available, (2) available for downward adjustment, (3) upward ramping capability requirement, (4) downward ramping capability requirement [29-32]. They measure the ability of the power system to cope with variable loads by calculating the regulation capacity and regulation rate of the power system in different directions.

The purpose of this paper is to propose an evaluation index based on system flexibility to fill the gap in the current evaluation system. This index takes system flexibility as the weight of prediction error. When the flexibility is low, the error weight is significant, while when the flexibility is high, the error weight is small. Four common system flexibility indexes are adopted, and the importance degree of different indexes is determined by using entropy weight method, and the flexibility matrix of the system is obtained after the summation of the indexes according to the importance degree and normalization treatment, so as to improve the existing evaluation indexes. The improved evaluation index can reflect the relationship between the prediction error and the system flexibility and has important guiding significance for the dispatching department to arrange the generation plan.

II. Methodology

In order to better evaluate the forecast level of renewable energy stations and guide the dispatching department to make generation plans, a model to quantify the flexibility of power system is established. Firstly, several system flexibility indexes are calculated according to the station information, then the importance of indexes is determined by entropy method, and the system flexibility is evaluated comprehensively. Finally, the system flexibility matrix is used to construct new evaluation indexes.

A. Calculate the system flexibility index

At present, most of the indicators of power system flexibility are designed based on the current up-or-down capacity of the system and the current up-or-down slope capacity. These four indicators can fully reflect the corresponding capacity of the system to variable load at a certain moment and can be used to represent the flexibility of the power system. Considering that the flexibility of power systems is variable and the measurement of flexibility is complex, in this paper, the day is divided into 96 time points, each time point interval is 15 minutes. The calculation formula of flexibility index is as follows:

Calculate the upward adjustable capacity available of system:

$$F_{upcap,t} = P_{\max,t} - NL_t \tag{1}$$

Where $P_{\max,t}$ is value of the system maximum force at time *t*, NL_t is value of the net load at time *t*.

The upward adjustable capacity available is the upward reserve capacity of the power system during operation. The larger the capacity, the more flexible the system will be, and the less affected by the prediction error. The smaller the capacity, the less flexible the system will be, and the more affected by the prediction error.

Calculate the capacity available for downward adjustment of system:

$$F_{downcap,t} = NL_t - P_{\min,t} \tag{2}$$

Where $P_{\min,t}$ is value of the system minimum force at time *t*.

The capacity available for downward adjustment is the downward reserve capacity of the power system during operation. The larger the capacity, the more flexible the system is; the smaller the capacity, the less flexible the system is.

Calculate the upward ramping capability requirement of system:

$$F_{uprate,t} = \forall (NL_t - NL_{t-\Delta t}) > 0 \tag{3}$$

NL_t is value of the net load at time *t*, Δt is value of the time interval.

Ramping capacity represents the regulation rate of the system. The larger the ramping capacity of the system is, the stronger the ability to adjust variable loads is and the better the flexibility of the system is.

The upward ramping capability requirement refers to the demand of load on the upward ramping capacity of the system. The higher the requirement, the lower the remaining upward ramping capacity of the system and the lower the system flexibility. On the contrary, the lower the requirement, the higher the remaining upward ramping capacity of the system, the higher the system flexibility.

Calculate the downward ramping capability requirement of system:

$$F_{downrate,t} = -(\forall (NL_t - NL_{t-\Delta t}) < 0) \tag{4}$$

The downward ramping capability requirement refers to the demand of load on the downward ramping capacity of the system. The higher the requirement, the lower the system flexibility. On the contrary, the lower the requirement, the higher the system flexibility.

The first two flexibility indicators are positively correlated with the system flexibility, the larger the index value is, the greater the system flexibility is, while the last two flexibility indicators are negatively correlated with the system flexibility, the larger the index value, the smaller the system flexibility.

B. *Entropy weight method is used to determine the influence degree of the flexible index*

In information theory, entropy is a measure of the uncertainty of information. The larger the amount of information, the smaller the uncertainty and the smaller the entropy. The smaller the amount of information, the greater the uncertainty and the greater the entropy. According to the entropy value of the sample, the dispersion degree of the index can be judged and the weight of the index can be determined. On the basis of the original indexes. Yao et al. determined the weights of different indexes by using the entropy method, constructed a multi-index evaluation system, eliminated the influence of human factors on the weight distribution of indexes, and could accurately evaluate the prediction level of different wind farms [33].

Entropy method is widely used to determine the importance of indicators. Its objective evaluation method can eliminate the subjective influence well and provide a basis for comprehensive evaluation. When the weight of multiple indexes cannot be calculated, entropy weight method is usually used to determine the importance of each index. Entropy method is used to calculate the information entropy of the index, which is represented as the degree of change of the index. The greater the degree of change, the stronger the disorder of the index and the bigger the weight of the corresponding index [34-35]. The entropy redundancy can be used to represent the importance of index. The basic steps are as follows.

Normalization processing to eliminate the differences in the values of different indicators:

$$X^k_{i,jnorm} = \frac{X^k_{i,j} - X^k_{i\min}}{X^k_{i\max} - X^k_{i\min}} \tag{5}$$

Calculate the proportion of indicators of samples:

$$P^k_{i,j} = \frac{X^k_{i,jnorm}}{\sum_{j=1}^{n=96} X^k_{i,jnorm}} \tag{6}$$

Calculate the entropy of indicators of samples:

$$e^k_i = -\frac{1}{\ln(n)} \sum_{j=1}^{n=96} P^k_{i,j} \ln(P^k_{i,j}) \tag{7}$$

Calculate entropy redundancy of indicators of samples:

$$d^k_i = 1 - e^k_i \tag{8}$$

Calculate the influence degree of the indicators:

$$w^k_i = \frac{d^k_i}{\sum_{k=1}^{n=4} d^k_i} \tag{9}$$

Where $X^k_{i,jnorm}$ is normalized value of the *k*-th index of the *j*-th point of the *i*-th sample. $X^k_{i\min}$ and $X^k_{i\max}$ are minimums and maximums of *k*-th index of *i*-th sample, *i* is the number of samples, and k is the number of indexes.

C. *Building the weight matrix*

According to the importance degree of each index calculated in the entropy weight method, the four indexes were added according to the calculated weight.

$$w_i = \sum_{k=1}^{n=4} X^k_{i,j} \times w^k_i \tag{10}$$

Where w_i is an error weight matrix based on system flexibility, it is the set of error weights for 96 time points.

The smaller the error weight is, the higher the flexibility of the system is and the lower the requirement for the prediction performance is. The larger the error weight is, the lower the flexibility of the system is and the higher the requirement for the prediction performance is.

D. *Summary of flexibility weight*

In order to measure the flexibility of the system more scientifically and construct the error weight matrix based on flexibility, this paper adopts the entropy weight method to determine the weight of different flexibility indicators, and the following steps are as follows:

Firstly, a matrix containing four flexibility indicators is established:

$$X = \{F_{upcap,t}, F_{downcap,t}, F_{uprate,t}, F_{downrate,t}\} \tag{11}$$

Where $F_{upcap,t}$ is upward adjustable capacity available, $F_{downcap,t}$ is Capacity available for downward adjustment, $F_{uprate,t}$ is upward ramping capability requirement, $F_{downrate,t}$ is downward ramping capability requirement.

Secondly, standardize each index, and use entropy weight method to calculate the weight of each index.

Thirdly, the flexibility matrix of the samples can be obtained by adding the flexibility indexes according to the weight of each flexibility index.

Fourthly, using the flexible row weight to correct the prediction error index.

The technical flow chart is shown in Fig. 1.

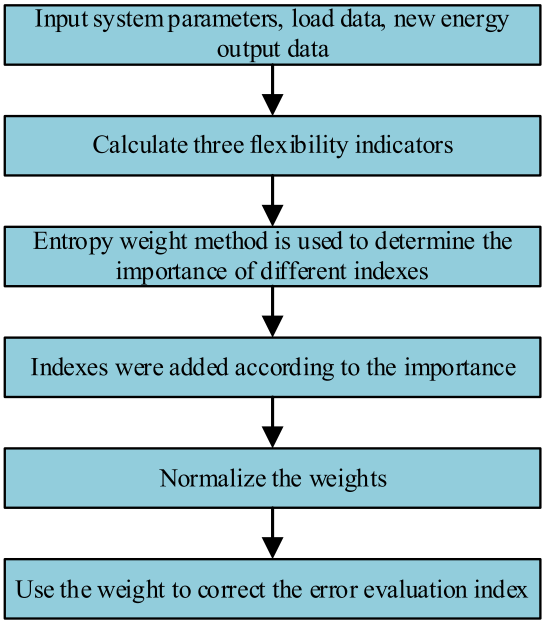

Fig. 1. Technical flow chart.

III. CASE STUDY

In order to further illustrate the guiding significance of the indicators proposed in this paper in the prediction and scheduling of renewable energy stations, this paper takes the operation data of a regional power grid in China in 2020 as an example for simulation. The data sampling period is 5 minutes.

A. *Calculate the weight matrix*

According to the load situation and the renewable energy output can be calculated to get the net load output, and then can determine the day of the unit output and the unit regulation rate. The flexibility index matrix can be calculated according to the flexibility index formula. According to the entropy method, the importance degree of flexibility indexes is calculated, and the system flexibility matrix of comprehensive evaluation is obtained. The system flexibility matrix is transformed into error weight matrix. The lower the system flexibility, the larger the error weight, the higher the system flexibility, the smaller the error weight. The error weight matrix is used to modify the existing evaluation indexes to get a new evaluation index Root Weighted Squared Error (RWSE).

$$E_{RWSE} = \frac{\sqrt{\sum_{i=1}^{n}(p_{tru} - p_{pre})^2 \cdot w_i}}{cap} \tag{12}$$

The error weight curve for a day in March is shown in Fig. 2.

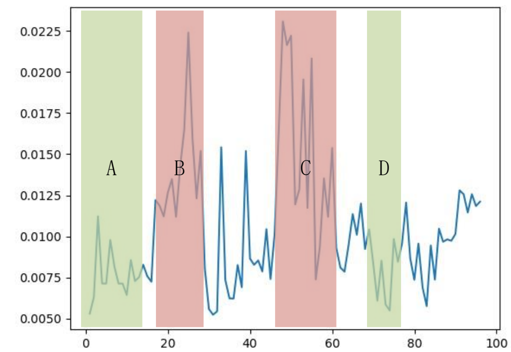

Fig. 2 The error weight curve for a day in March.

When a large amount of renewable energy penetrates into the power system, it will have a great impact on the flexibility of the operation of the power system and make it difficult to make the generation plan. Therefore, it is very important to analyze the flexibility of the power system. It can be seen from Fig. 2 that on this day, the error weights of period B and C are relatively high, which indicates that the system is less flexible in this period and the system is greatly affected by the prediction error. In the other period, the error weights of period A and D are low, which indicates that the system has high flexibility in this period and can tolerate certain prediction errors.

B. *Application of index in photovoltaic power plant*

Comparison of power prediction of the two scenarios is shown in Fig. 3, The system flexibility of the two scenarios is shown in Fig. 4.

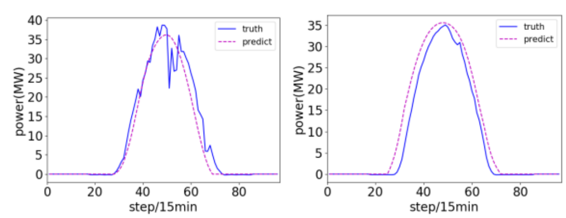

Fig. 3 Comparison of the two scenarios.

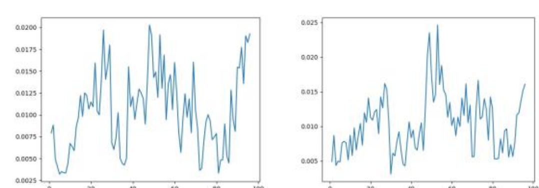

Fig. 4 Comparison of the system flexibility of the two scenarios.

Scenario 1 is on March 6th and Scenario 2 is on November 7th. Fig. 2 shows the prediction comparison of two scenarios. The prediction of Scenario 1 fluctuates greatly while that of Scenario 2 changes gently. Fig. 3 shows the error matrices of two scenarios. In scenario 2, the moments of system flexibility shortage are mainly concentrated in the morning and afternoon, while in scenario 3, the moments of system flexibility shortage are mainly concentrated in the afternoon.

Comparison of evaluation indexes of the two scenarios is shown in Fig. 5.

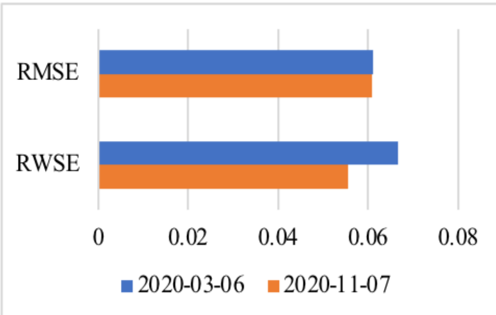

Fig. 5 Comparison of evaluation indexes of the two scenes.

As can be seen from Fig. 5, RMSE of the two scenarios has little difference, and the prediction degree of the two scenarios cannot be distinguished by RMSE index. However, the same prediction error will have different effects on different systems. Comparison of prediction for a couple of days can be found a scene in the afternoon there was a larger prediction error, the flexibility of the system is in shortage state, at this time should be strictly monitored, scenario 2 in most schedule shows good prediction accuracy, especially in the afternoon session, no large deviation, can say scene two prediction error's influence on the system than the impact of setting a prediction error. However, RMSE does not do a good job of representing this difference. Fortunately, using RWSE does a good job of distinguishing them. The index RWSE is designed based on the flexibility of the system. When the flexibility of the system is low, the prediction accuracy is strictly monitored, which can well reflect the impact of the prediction error on the power system and provide support for measuring the prediction situation of the station.

C. *Application of index in dispatching department*

Three photovoltaic power plants (F1, F2, F3) in a province of China were selected for analysis, and the station capacity was all 50 MW.

The power prediction of different stations on typical days and the system flexibility of that day are shown in Fig. 6, Index comparison of the stations is shown in Fig. 7.

Fig. 6 shows the power prediction of F1, F2 and F3 stations on a certain day and the flexibility of the system on that day. Fig. 7 shows that the prediction work of the three photovoltaic stations is ranked from good to bad, by using RMSE is F3, F1, F2, and by using RWSE is F1, F3, F2.

According to the ranking of the two indexes, the prediction accuracy of F2 station is the lowest. As can be seen from the prediction of F2 station in Fig. 6, a large error occurs at noon, and the error fluctuates greatly, which also has a great impact on the system. For F1 station and F3 station, compared with RMSE value, the prediction accuracy of F3 station is better than that of F1 station. However, at noon, when the system flexibility is higher, the prediction effect of F1 station is better and it is more friendly to the system. Therefore, from the perspective of the influence of the prediction error on the system flexibility, the prediction of F1 station is better than that of F3 station, and the prediction effect of F2 station is the worst.

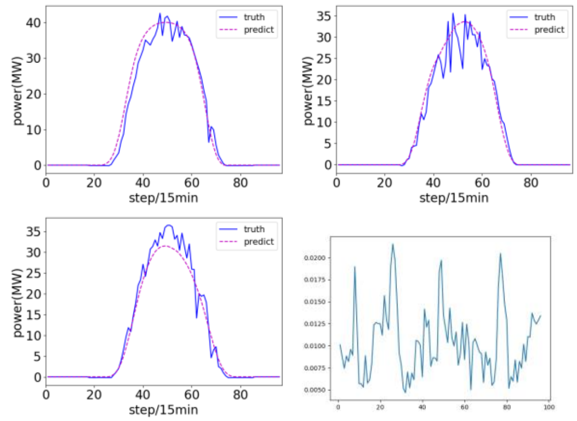

Fig. 6. Comparison of typical daily forecasts.

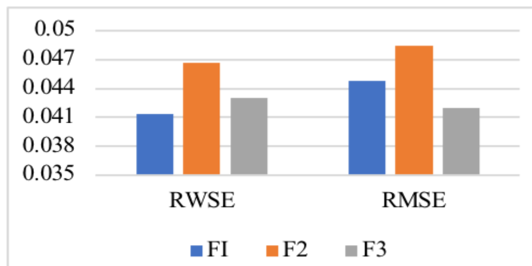

Fig. 7. Comparison of typical daily error indicators.

When the dispatching department makes the generation plan, it considers more about the influence of the forecast situation on the flexibility of the power system. Compared with RMSE, RWSE can better show the relationship between the prediction error and the flexibility of the system, and it is more suitable for guiding dispatching.

IV. Conclusion

The traditional power prediction evaluation index can not reflect the relationship between the prediction error and the system flexibility. In this paper, several power system flexibility indexes are integrated to reflect the system flexibility more comprehensively and effectively, and used to construct a new evaluation index RWSE.RWSE does not need to divide the time period manually, and it is more objective, stable and has great application potential than the time period considering the influence of prediction error. This index can evaluate the accuracy of power prediction according to the flexibility of the system, and has a good performance in measuring the prediction level of single station and scheduling of multiple stations.

In other words, RWSE index maintains the objectivity and adaptability of RMSE index, introduces the system flexibility, is a supplement to the original evaluation system, and provides a scientific and reasonable guidance for the prediction of renewable energy stations.

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