Proceedings Paper:

Zhu, J-H, Li, K orcid.org/0000-0001-6657-0522, Xu, R et al. (3 more authors) (2021) Energy Storage Capacity Optimization for Deviation Compensation in Dispatching Grid-Connected Wind Power. In: Recent Advances in Sustainable Energy and Intelligent Systems: 7th International Conference on Life System Modeling and Simulation, LSMS 2021 and 7th International Conference on Intelligent Computing for Sustainable Energy and Environment, ICSEE 2021, Han. 7th International Conference on Life System Modeling and Simulation, LSMS 2021 and 7th International Conference on Intelligent Computing for Sustainable Energy and Environment, ICSEE 2021, 30 Oct - 01 Nov 2021, Hangzhou, China. Springer, Singapore , pp. 97-109. ISBN 978-981-16-7209-5

https://doi.org/10.1007/978-981-16-7210-1_10

Energy Storage Capacity Optimization for Deviation Compensation in Dispatching Grid-Connected Wind Power

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Abstract: There exist many uncertain factors in wind power forecasting, often resulting in large prediction errors. Various prediction technologies have been developed to reduce errors and improve the dispatch-ability of grid-connected wind power. To install energy storage systems is an effective approach to reduce the scheduling deviation in dispatching the grid-connected wind power. This paper considers the optimal capacity allocation, a key issue in smoothing the grid wind power generation and integration. Based on the analysis of wind power prediction technologies and the resultant prediction deviations, the relationship between the distribution characteristics of wind power prediction errors and energy storage capacity demand is first investigated. Then, an optimization method is proposed, considering the stability of grid operation and the relationship between compensation necessity and load changes. Further, load fitness factor is introduced in processing the deviation data samples, and an economic dispatch model is introduced for the deviation compensation, considering the operation costs. Finally, based on the analysis of various factors, the technical route to achieve energy storage capacity allocation for scheduling deviation compensation is developed. Case studies are presented to demonstrate the effectiveness of the proposed approach.

Keywords: wind power dispatching; deviation compensation; prediction error distribution characteristics; storage capacity

1 Introduction

Wind power generation and integration has been intensively researched and rolled out worldwide in the last decade. The power generated from a fixed wind turbine mainly depends on the local wind speed, direction, wind pressure and other weather conditions, as well as geographical environmental factors. The performance of wind turbine models are often limited by the uncertainties imposed on both the model inputs and outputs while the conventional numerical weather forecasting methods also have low accuracy on localized regions. It is therefore difficult to accurately predict the actual wind power generation.

However, the power system dispatch always relies on the predicted data, it is therefore vital to improve the wind power prediction techniques. The early wind power prediction models often use wind speed information and experimental curves, which sometimes are also referred to as the physical methods. The second category is statistical methods, most of which rely on historical data [1-2]. The third category is intelligent algorithms, where machine learning rules are used to establish the relationship between input and output, such as SVM and ELM, etc. [3-5]. Now, kinds of intelligent combination algorithms are emerged [6-7].

All the existing literatures demonstrated that the prediction accuracy has improved with the development of technology, but the demand for data processing speed and memory has also been increased simultaneously. Although the prediction error has been decreased to a certain extent, the absolute error is still on the rise inevitably with the significantly increased installed capacity of wind power. Consequently, the increased un-schedulable wind power deviation greatly affects the balance of supply and demand of the power grid, bringing unstable factors to the grid. The increased reserve capacity must be installed to suppress the unpredictable deviations originated from the wind power integrated in the grid, which increases the cost of grid operation. On the other hand, the inefficient use of standby units is either a waste, especially, the thermal power generation units that consume coal resources has exacerbated the depletion of limited nonrenewable energy resources and their environment impact. As a countermeasure, national system operators such as the National Energy Administration in China issue functional specifications on the wind power prediction systems [8].

As an effective measure to tackle the problem of wind power scheduling deviations, energy storage technologies have drawn much attention in recent years due to their great potential of flexible throughput characteristics. However, due to the sheer demand for a significantly huge amount of storage capacity for deviation compensation, it is practically challenging to adopt energy storage to reduce the scheduling deviation of wind power and turn un-schedulable into schedulable. The concept was proposed for about 20 years, and a number of results have been presented for scheduling deviation compensation. As shown in Table 1, under the consideration of different factors for scheduling deviation compensation, the capacity allocation of energy storage accounts from 19.8% to 60% of the wind power capacity.

Table 1 Energy storage configuration for deviation compensation

Scheduling compensation technology	Wind power capacity / MW	Statistical span / h	Storage configuration / MAh	Compensation target	Actual results
Kernel density estimation followed by GA-ANFIS prediction error statistics [9]	148.5	48	89, confidence level 80%	Small prediction error,	MAE and RMSE 6.70%, 9.15%
Based on feature extraction and LSSVM MPC [10]	49.5	1/4, 1/3, 1/2	9.8	Grid-connected operation cost-effectively	Full compensation
Exceeding error frequency weight (EEFW) combined with three-dimensional optimization method [11]	148.5	24	35.3	Degree of wind power compensation, energy storage life, economic ratio of hybrid storage capacity	Prediction error ≤15%, wind power fluctuation ≤ 20%
Two-stage stochastic optimization framework [12]	3.6, 2 × 170 kW diesel generators at minimum load	24	1.81	wind speed and the load growth rate, load balancing and frequency control	Life cycle cost varies very slightly with the number of scenarios (less than 1%)
Based on comprehensive cost-benefit model [13]	200	24	60.5	Ease the peaking burden, smooth load curve, and reduce the thermal power coal consumption.	Adapting to presupposed dispatching schedule

The dynamic throughput of energy storage depends on the positive and negative offset of the scheduling deviation, not only the polarity of the bias, but also the magnitude, so the cumulative amount of deviation directly impacts on the overcharge and over-discharge characteristics of the energy storage system. In the case that the predicted wind power is in the power dispatch, the input and output throughput of energy storage not only depends on the prediction technology, but also the uncertainties of the key factors such as the wind speed, the superimposed effect arisen from these important factors directly determines the energy storage capacity allocation. It is therefore necessary to investigate the deviation distribution characteristics.

2. The impact of scheduling deviation distribution characteristics on energy storage capacity allocation

Energy storage capacity is used to deliver the throughput of the entire charging and discharging cycle. Due to the irregular and continuous alternation of positive and negative deviations, it is quite challenging to determine the desired energy storage capacity. Grid scheduling performance is heavily affected by the prediction technique. Positive and negative polarity changes of scheduling deviations imply the dynamic requirements on energy storage charging and discharging. Therefore, it is necessary to investigate the relationship between deviation distribution characteristics and energy storage capacity demand.

2.1 Error distribution analysis

The capacity analysis of the energy storage system is obviously a key prerequisite for the realization of schedulable wind power. Positive or negative deviation fluctuation within a sampling period renders the fluctuation of the capacity amplitude, while continuous positive or negative deviations implies that the energy storage system needs to absorb or release the accumulated energy continuously. Obviously, if the wind power prediction is directly used in the grid power dispatch, the distribution characteristics of the prediction errors determine the demand for energy storage capacity. Continuous positive or negative errors will inevitably increase the energy storage capacity for deviation compensation. Several error compensation distribution characteristics are shown in Fig. 1, such as ARIM（Autoregressive Integrated Moving Average model） [14], BPNN（Back-propagation Neural Network） [15], PSO（Particle Swarm Optimization） [16], SVM（Support Vector Machines） [17], EEMD（Ensemble Empirical Mode Decomposition） [18], ELM（Extreme Learning Machine） [19], WNN（Wavelet-based Neural Network） [20], RBPNN（Radial Basis Function Neural Network） [21], RBF（Radial Basis Function） [22], LSSVM（Least Squares Support Vector Machines） [23], GM （Gray Forecast Model) [24], MCC（Matthews Correlation Coefficient) [25]. As shown in Fig.1, the error distribution characteristics varies in different time periods, and some continuous intervals have the same polarity, which implies that the energy storage system needs to be charged or discharged continuously, leading to a large cumulative value, and thus the energy storage system needs to have a larger rechargeable or re-dischargeable capacity requirement. While for some intervals, the polarity of the deviations alternate frequently, which implies that the energy storage system is subject to alternating charge and discharge. The energy storage capacity is determined by the maximal cumulative value of the positive and negative deviations. If the positive and negative deviations are symmetric, the capacity of the energy storage system only needs to accommodate the maximal cumulative energy of a single charge or discharge phase, and thus the capacity requirement is relative small. However, in practice it is difficult to develop a wind power prediction technology which exhibits a symmetric error distribution characteristics, and in most cases the prediction error distribution is asymmetrical. If the overall error amplitude is small, the prediction technology still has lower requirements for the energy storage capacity for deviation compensation. On the other hand, frequent positive and negative changing in prediction errors implies that the energy storage system has to be charged and discharged frequently, which will affect the service life of energy storage. Overall, a general conclusion can be drawn that storage capacity demand for error compensation largely depends on the error distribution characteristics.

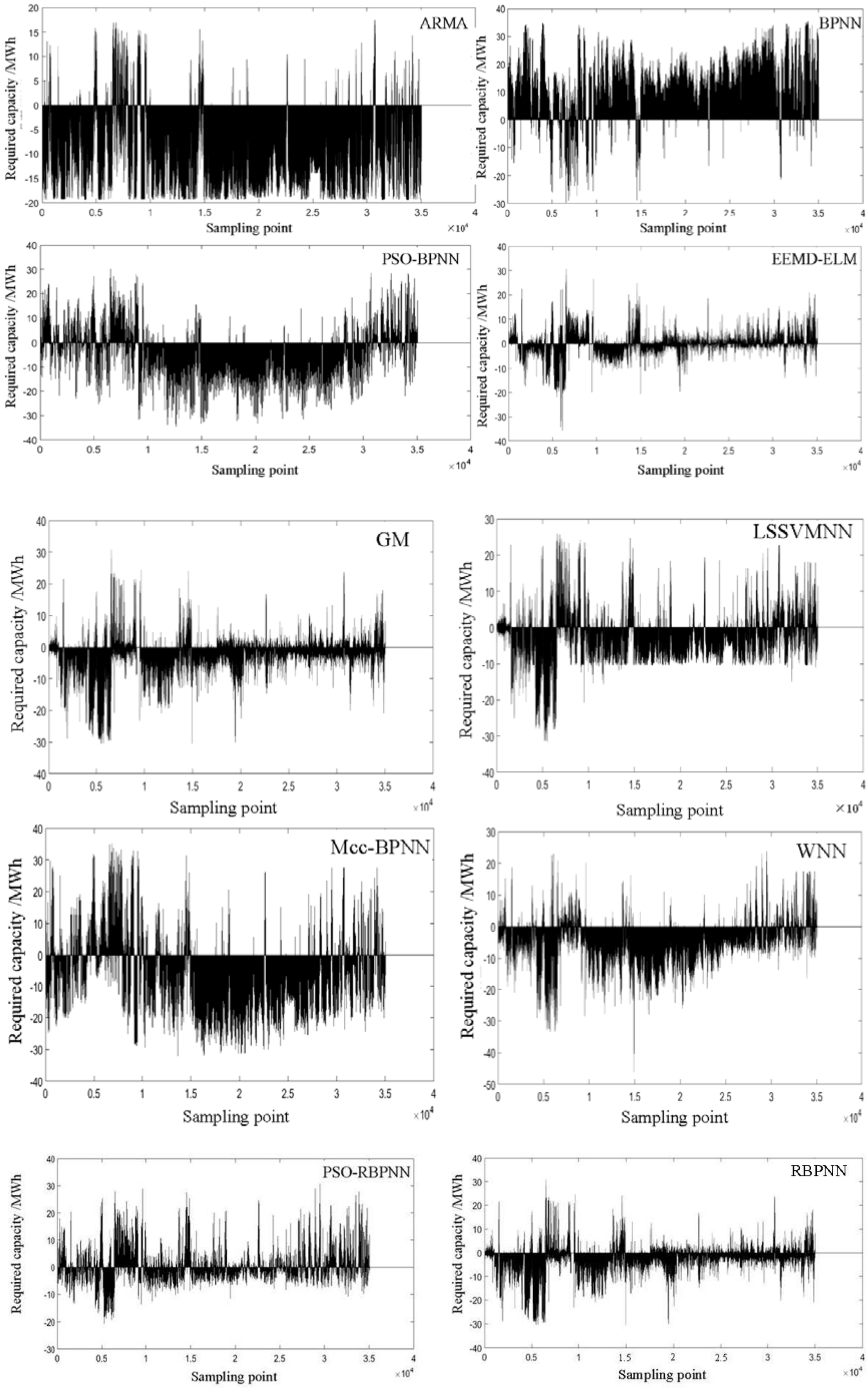


Fig.1 Sampling time prediction deviation compensation demand distribution

while large errors requires large storage capacity, while small errors do not necessarily imply small capacity as their cumulative values can still be very large.

Symmetrical error distribution but with frequent polarity alternations is not necessarily a good prediction technique from the energy storage configuration prospective. Take 24 hours statistics of 4 algorithms as an example, the cumulative capacities are shown in Fig. 2. A desired error distribution for energy storage configuration could be the case where polarity of the prediction errors alternate at certain interval, symmetrically, and the amplitude should not be too large as well.

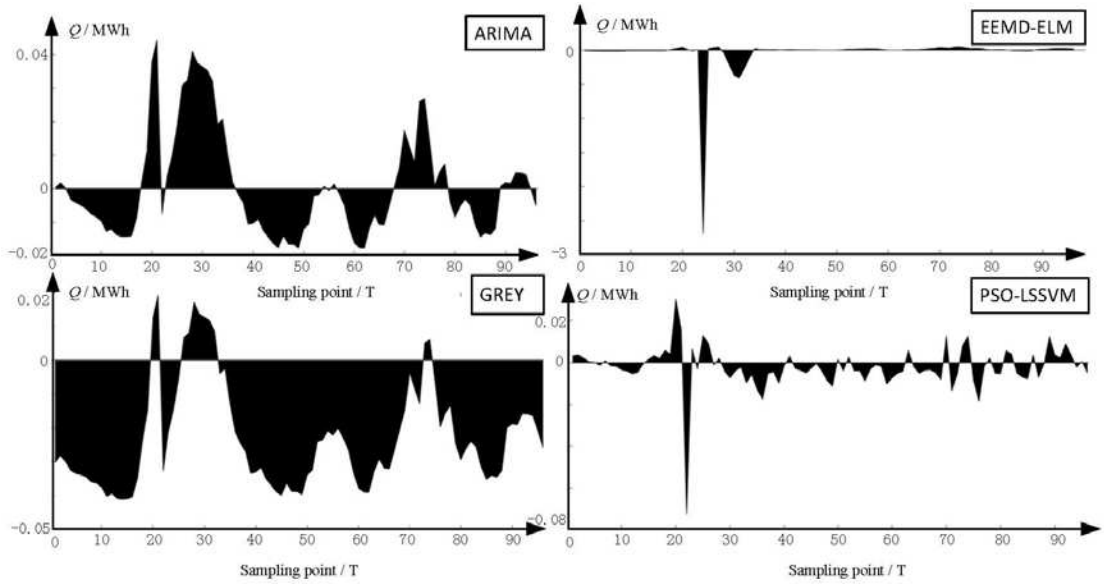


Fig.2 Cumulative power prediction error

2.2 The energy storage capacity demand for deviation compensation

The statistics of the actual cumulative power prediction errors of typical day, typical month, and a year have been analyzed for a 1.5 MW wind turbine using different wind power prediction methods. As shown in Table 2, it is evident that the prediction error variations are uncertain for different time intervals, but the cumulative errors increase with the time scales. It is also evident that different prediction algorithms and different time scales require different energy storage configurations.

Table 2 Capacity demand for power deviation compensation of all periods (kWh/kW)

Statistical span	Predictive technology										
	BPNN	MCC-BPNN	PSO-BPNN	RBFNN	PSO-RBFNN	W-NN	LS-SVM	ARIMA	EEMD-ELM	Grey	PSO-LSSVM
Typical day	191/74	219/67	429/78	1393/111	1233/78	1052/62	1097/99	2130/125	948/65	2357/134	1242/112
48 hours	1558/77	1822/95	1087/72	1752/80	1499/70	1751/65	1139/96	3047/124	1247/64	3558/135	891/99
Typical month	6381/136	27314/141	12060/126	5057/121	9508/112	11463/134	5315/113	11440/95	6778/142	14646/100	7618/123
Year	436918/142	260867/141	232675/138	41789/121	12756/123	206406/145	117619/126	171510/97	22799/142	245293/100	99510/123

3. Optimal energy storage capacity allocation considering load variation and operating costs in power system dispatch

Since the integration of energy storage can support the scheduling of wind power integrated into the grid and smooth the variation characteristics of the prediction deviations, it is possible to holistically consider the changes in grid load, the expected income of wind power operators, and the operation characteristics of energy storage to achieve optimal scheduling. As shown in Fig.3, the scheduling deviation compensation can be considered together with the load demand, peak shaving, economy profit, *SOC* (state of charge), and energy storage operation cost.

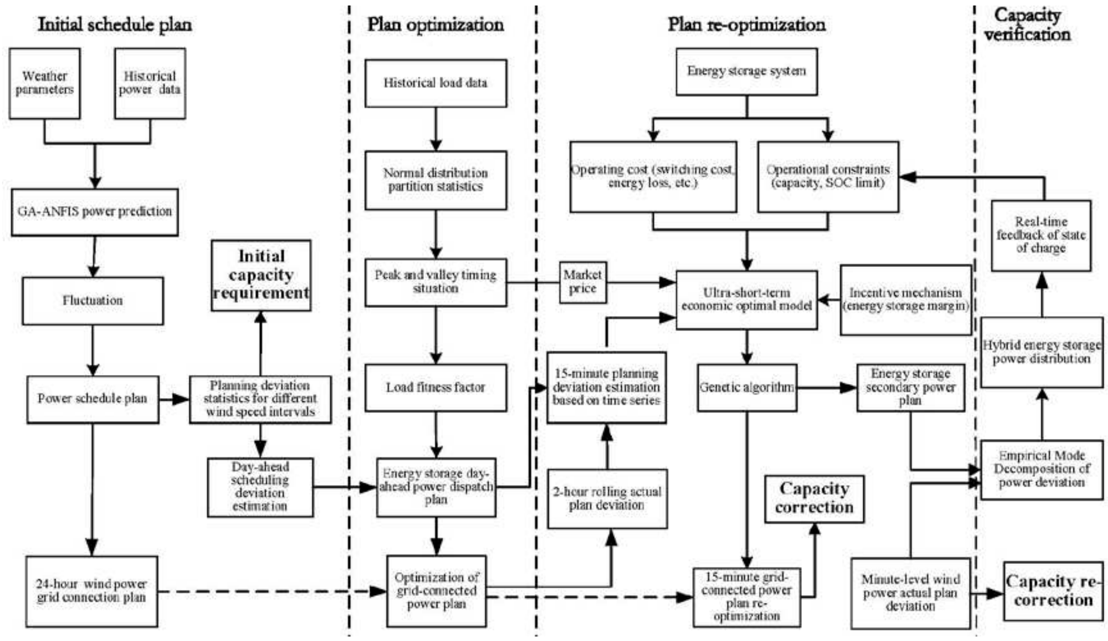


Fig 3. Energy storage capacity configuration considering different scheduling methods

3.1 Scheduling optimization considering load variations

If the distribution characteristics of the deviations of the schedule wind power coincide with the characteristics of the load variations, this power deviation can help the grid with peak shaving. However, if the scheduled power is higher than the actual peak power consumption, this difference needs to be eliminated. Therefore, in order to calculate the energy storage capacity allocation, load variations must be considered. In addition to the peak period, the deviation correction needs to consider the trend of load variations and make appropriate adjustments by using the energy storage, while reducing the number of charging and discharging switching times, thus increase the service life of the energy storage system. Further, the dispatching results and revenue costs are also affected by load variations to some certain extent. Wind power prediction deviations and dispatching behavior therefore need to can be considered holistically to determine the energy storage capacity. The deviation compensation method considering the load variations is given as follows. The value of the load fitness factor is given shown in Table 3.

$$\begin{cases} P_{s,t}^{s} = P_{c,t}^{s} + \left(1 - r_{n}\right) \cdot \Delta P \\ \Delta P = P_{c,t}^{s} - P_{a,t}^{s} \end{cases} \tag{1}$$

Table 3 Load fitness factor value r_n

Load period distribution	Scheduling deviation (ΔP) and grid load change trend (*K*)								
	$\Delta P>0$ and $K\geqslant 1$	$\Delta P>0$ and $0<K<1$	$\Delta P\neq 0$ and $K=0$	$\Delta P>0$ and $-1<K<0$	$\Delta P>0$ and $K\leqslant -1$	$\Delta P<0$ and $K\geqslant 1$	$\Delta P<0$ and $0<K<1$	$\Delta P<0$ and $--1<K<0$	$\Delta P<0$ and $K\leqslant -1$
Valley periods	1/3	1/4	1/8	0	0	1/4	1/2	3/4	1
Transition periods	1	2/3	¾	1/4	1/8	1/2	3/4	1/2	1
Peak periods	1	1	1	1/2	1/4	0	0	1/4	1/2

where $P_{s,t}^{s}$ is the compensated scheduling power after considering the load variations, $P_{c,t}^{s}$ is the initial scheduled power, $P_{a,t}^{s}$ is the actual wind power output during the period (refer to historical data), r_n is the load fitness factor considering the deviations. The value in the table not only considers the load change trend in different periods, but also considers the polarity of the deviation.

3.2 Scheduling optimizing considering operating costs

From the electricity market operation perspective, in addition to the grid-side load variations, the energy storage configuration must also consider the economic benefits of wind power operators. Therefore, it is necessary to study the energy storage operating costs and grid-connected power generation benefits of the deviation compensation scheme, and optimize the energy storage configuration to achieve high-accuracy schedule implementation. Aimed at maximizing the profit Z of the wind power system, and the following formula (2) is arrived.

$$\max Z\left[\sum_{t\in T} f\left(s, P_{d,t}\right)\right] = \max \sum_{t=1}^{T}\left[Z_{\mathrm{a,t}}^{s} - Z_{\mathrm{bq,t}}^{s} + Z_{\mathrm{se,t}}^{s} - Z_{\mathrm{loss,t}}^{s} - Z_{qs,t}^{s} - Z_{\mathrm{tz,t}}^{s} + Z_{st,t}^{s}\right] \quad (2)$$

where, s represents the uncertain scenario of the scheduling scheme, T is the number of time segments in a day, $Z_{\mathrm{a,t}}^{s}$ is the daily benefit of a scheduling output, $Z_{\mathrm{bq,t}}^{s}$ is the penalty cost of daily scheduling of wind energy, $Z_{\mathrm{se,t}}^{s}$ is the exchange cost of energy storage power, $Z_{\mathrm{loss,t}}^{s}$ is the loss cost of energy storage exchange power, $Z_{qs,t}^{s}$ is the frequent switching cost of energy storage, $Z_{\mathrm{tz,t}}^{s}$ is the upfront investment cost of energy storage, and $Z_{st,t}^{s}$ is the incentive premium.

4. A case study

The historical operation data of a wind farm are used in the case study, and the initial storage capacity is 148.5 kW. The rated voltage of the battery and the super capacitor are 180V and 160V respectively. One year data are selected to train and test energy storage capacity required to compensate for the deviations of different grid-accessed schedule, including the direct scheduling for stabilizing the grid after prediction, primary optimization combined with grid load sequence distribution, and the re- optimization under joint consideration of economic dispatch costs. Several scheduled power curves and actual power curves, the original predicted power curve, and the wind/storage power curve are illustrated in Fig. 4. The change curve of energy storage *SOC* used for scheduled power deviation compensation of one day is as shown in Fig. 5, where the number of 10~11h sampling points is around 1.25-1.375 (10^5), while the number of 14~15h sampling points is around 1.75-1.875 (10^5), for 21~22h it is about 2.75-2875 (10^5).

As shown in Fig. 4, the power prediction curve exhibits dramatic fluctuations. If the load variation is considered, the compensation is increased during peak hours (10~11h, 14~15h, 21~22h), while the volatility of the scheduled curve is slightly higher than that of the initial scheduling, the maximum volatility, which has increased by about 3%. After increasing the compensation, the overall tendency is the discharge behavior, as shown in Fig. 5(b). This reveals that the degree of compensation increases significantly after the load fitness factor is added into the cost function. This implies that it is insufficient to just consider the load factor and it is also necessary to consider various economic factors in the objective function. After the model is optimized, charge and discharge behavior can maintain the *SOC* of the energy storage system at about 50%, as shown in Fig. 5(c).

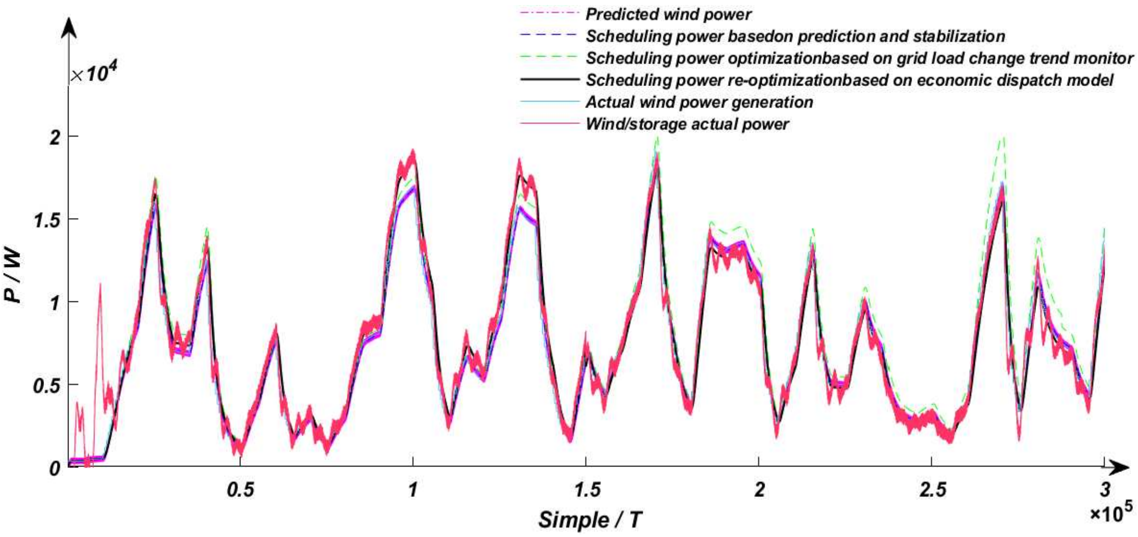
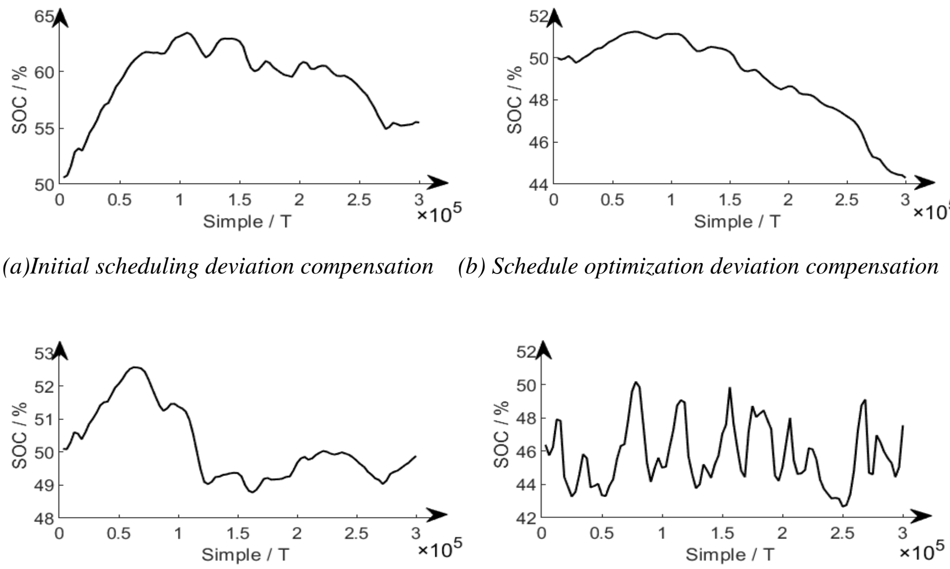


Fig.4 Power curves of scheduling and actual output



(a)Initial scheduling deviation compensation *(b) Schedule optimization deviation compensation*

(c) Schedule re-optimization deviation compensation *(d) Actual deviation compensation*

Fig.5 Hybrid energy storage *SOC* changes corresponding to several scheduling strategies

Among three different compensation schemes, the variations in the *SOC* curves due to the scheduling amendment are the smoothest, thus significantly reduced the energy storage capacity requirement. The deviation index is also decreased, and MAE and RMSE under the re-optimized scheduling is reduced by around 1.6% and 0.22%, leading to the reduction in energy storage capacity allocation, as shown in Table 4.

Table.4 Power scheduling indexes

Technology	Capacity		Accuracy		Volatility		Reported pass rate	
	Battery /kWh	Super capacitor /kWh	MAE /%	RMSE /%	Maximum volatility /%	Average volatility /%	r1 /%	r2 /%
Stabilization followed by prediction	3.78	2.24	9.4624	1.1689	2.0349	0.1031	81.36	97.68
Consider load fitness	3.52	1.6	8.7692	1.1085	4.9724	0.0634	95.48	100
Consider economic dispatch	1.26	2.0	6.9959	0.8488	3.6459	0.0622	98.97	100

Table 4 reveals that the energy storage capacity requirement of optimized scheduling deviation compensation is lower than the capacity requirement before optimization, total actual capacity be reduced by about 15% and 36% respectively. Meanwhile, the proportion of super-capacitors in the total capacity has also increased. This can effectively utilize the characteristics of super-capacitors and have certain economic benefits. At the same time, the MAE and the RMSE after the re-optimization are reduced by about 1% and 0.12% than that of the initial schedule, respectively, and more than 0.7% and 0.04% of the primary optimized scheduling. The re-optimization is better from the aspect of accuracy. However, from the point of view of volatility, the initial schedule is the largest, while the maximum volatility and average volatility are reduced by 0.7% and 0.01% respectively after model re-optimized. In regards to the accuracy and pass rate, the accuracy of the schedule has been steadily increased after consideration of the load adaptability and model re-optimization.

5. Discussions and conclusions

Due to the cumulative effect of the throughput characteristics of energy storage operation and the wind power scheduling deviation distribution, the capacity allocation technology used for scheduling deviation compensation mainly depends on the scheduling method. Different scheduling methods will lead to different distribution characteristics of the power deviations. Therefore, the demand for energy storage capacity is also different due to the following specific influencing factors.

1) The distribution characteristics of scheduling deviations corresponding to different prediction technologies, including changes in amplitude and polarity.

2) The scheduling technology, which leads to different distribution characteristics of the scheduled deviations.

3) The intervals of the wind power dispatch.

4) The initial value setting of the *SOC* of energy storage according to different scheduling strategies.

It should be noted that other factors also need to be considered, such as the feasibility of capacity configuration which directly depends on the operation mode and energy management method of the subsequent energy storage. Inappropriate operation control may directly deteriorate the efficiency of existing energy storage system. To achieve economic operations, effective energy management system combined with on-site wind power operation must be put in place.

6. Acknowledgements

This work is a part of the National Natural Science Research Programs of China (No. 61673226), considerable Natural Science Research Projects of Colleges and Universities in Jiangsu Province of China (No. 18KJA470003), Natural Science Foundation of Jiangsu Province (BK20200969), Nantong Science and Technology Bureau Project (JC2018116), and Jiangsu Province's fifth ‘333 high-level talent training objects’ Project. The authors would like to thank for the supports from both the Ministry of Science and Technology and National Natural Science Foundation of China.

7. Patents

Chinese invention patents are resulting from the work as follows:

1. Wind/storage integrated power dispatching scheduling optimization realization method. Authorization number: ZL 202010782421.x. Authorization date: 2021/03/26.
2. A hybrid energy storage power distribution method for improving wind power dispatch reliability. Authorization number: ZL 201911165452.4. Authorization date: 2020/12/08.
3. A method for determining hybrid energy storage capacity of Microgrid system load reliable power supply. Authorization number: ZL 201911397312.X. Authorization date: 2020/12/08.

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