

This is an Open Access document downloaded from ORCA, Cardiff University's institutional repository: <https://orca.cardiff.ac.uk/id/eprint/167732/>

This is the author's version of a work that was submitted to / accepted for publication.

Citation for final published version:

Ju, Liwei, Bai, Xiping, Li, Gen, Gan, Wei, Qi, Xin and Ye, Fan 2024. Two-stage robust transaction optimization model and benefit allocation strategy for new energy power stations with shared energy storage considering green certificate and virtual energy storage mode. Applied Energy 362 , 122996. 10.1016/j.apenergy.2024.122996

Publishers page: <http://dx.doi.org/10.1016/j.apenergy.2024.122996>

Please note:

Changes made as a result of publishing processes such as copy-editing, formatting and page numbers may not be reflected in this version. For the definitive version of this publication, please refer to the published source. You are advised to consult the publisher's version if you wish to cite this paper.

This version is being made available in accordance with publisher policies. See <http://orca.cf.ac.uk/policies.html> for usage policies. Copyright and moral rights for publications made available in ORCA are retained by the copyright holders.



Two-stage robust transaction optimization model and benefit allocation strategy for new energy power stations with shared energy storage considering green certificate and virtual energy storage mode

Liwei Ju^{a,b,*}, Xiping Bai^{a,b}, Gen Li^c, Wei Gan^d, Xin Qi^{a,b}, Fan Ye^e

a. School of Economics and Management, North China Electric Power University, Changping Beijing, 102206, China

b. Beijing Key Laboratory of New Energy and Low-Carbon Development (North China Electric Power University), Changping Beijing, 102206, China

c. Department of Engineering Technology and Didactics, Technical University of Denmark (DTU), 2750 Ballerup, Denmark

d. School of Engineering, Cardiff University, Cardiff, CF24 3AA, United Kingdom

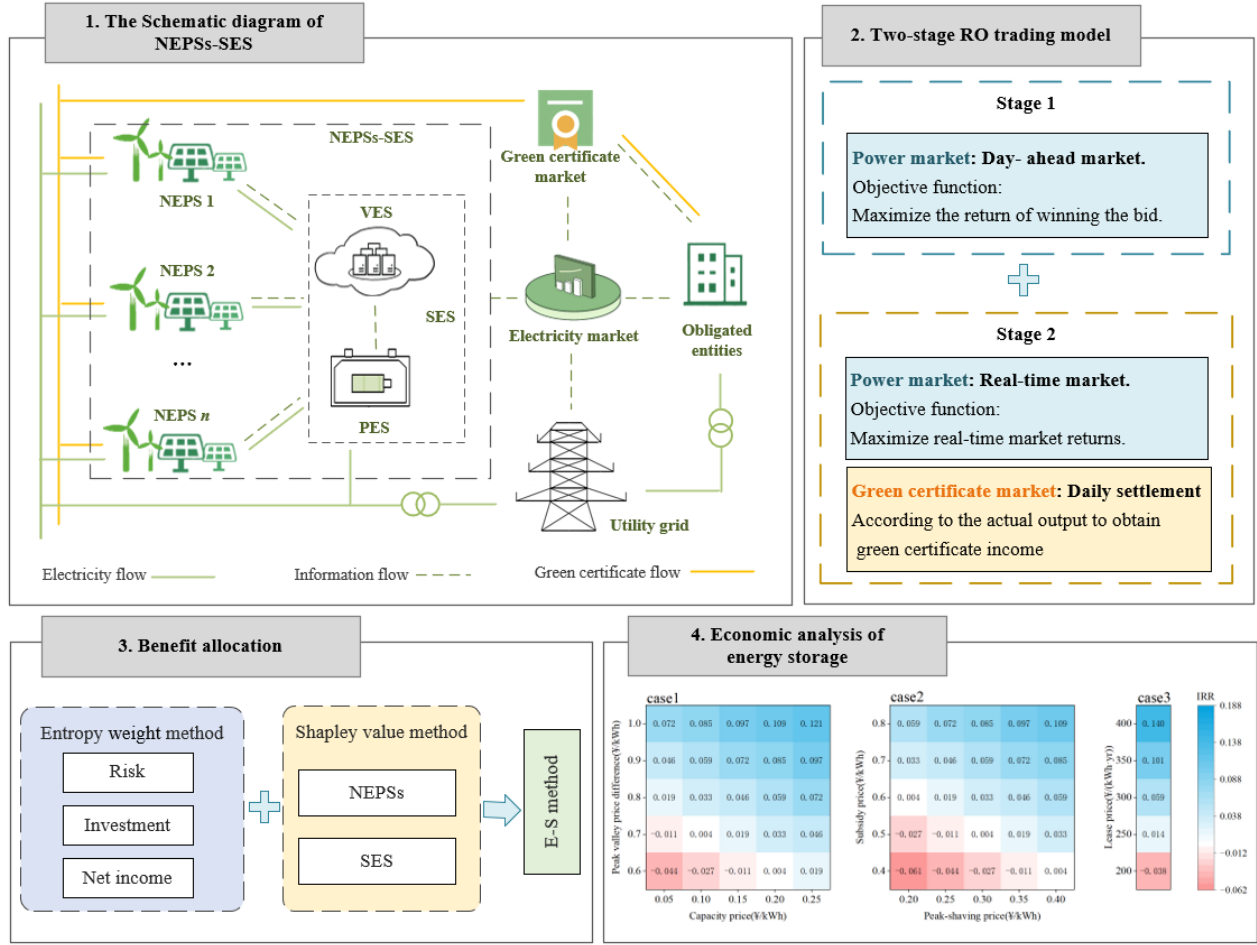
e. State Grid Jiangxi Extra High Voltage Company, Nanchang 330096, China

*Correspondence: jlw@ncepu.edu.cn. Tel.: +86-176-0016-0816

ABSTRACT: In the context of the large-scale participation of renewable energy in market trading, this paper designs a cooperation mode of new energy power stations (NEPSs) and shared energy storage (SES) to participate in the power-green certificate market, which divides SES into physical energy storage and virtual energy storage. Secondly, combining the advantages of scenario generation and robust optimization (RO), a two-stage RO model with improved uncertainty interval is proposed to determine the optimal trading strategy. Then, to better align the distribution results of cooperative benefits with the actual contributions of NEPSs and SES, an entropy weight modified Shapley value benefit allocation strategy is constructed. Finally, the new energy base in Qinghai Province, China is chosen for simulation. The results show: (1) Adding energy storage and using two-stage RO are able to effectively improve the ability of NEPSs to resist uncertainty, which increases the revenue of the alliance by 22.8%. (2) The application of SES has better economic benefits than each member equipped with energy storage separately. Compared with the latter, the deviation penalty cost of the former is reduced by 66.4%, and the revenue is increased by 3.4%. (3) The proposed entropy weight modified Shapley value method embodies the important auxiliary role of SES more obviously. Based on this method, the overall satisfaction of the alliance increases by 12.6%. Generally speaking, the optimization model and benefit allocation strategy proposed in this paper can provide guidance for NEPSs and SES participating in power trading, and promote the low-carbon transformation of the power sector.

Keywords: Variable renewable energy; Shared energy storage; Two-stage robust optimization; Benefit allocation

Graphical abstract:



NOMENCLATURE:

Abbreviations			
NEPSs	New energy power stations	CDF	Cumulative Distribution Function
SES	shared energy storage	WPP	wind power plant
RO	robust optimization	PV	photovoltaic
NEPSs-SES	new energy power stations cooperating with shared energy storage	MILP	mixed integer linear programming problem
DAM	day-ahead market	C&CG	Column and Constraint Generation algorithm
RTM	real-time market	LP	Linear Programming
SO	stochastic optimization	MP	master problem
SG	scenario generation	SP	subproblem
LHS	Latin hypercube sampling	E-S method	entropy weight modified Shapley value method
PES	physical energy storage	NIPK	net income per kwh
VES	virtual energy storage	IRR	internal rate of return
PDF	probability density function	NPV	net present value

1 Introduction

The western and northern regions of China abound in renewable energy sources, boasting significant development potential [1]. In order to further harness resources in remote areas and reduce carbon emissions, China has outlined a crucial policy in the energy sector: the establishment of a new power system primarily driven by new energy sources [2]. Therefore, there is a need to focus on studying the approaches and benefits of new energy power stations (NEPSs) participating in the electricity market. NEPSs collectively refer to all large-scale renewable energy generation systems, including wind farms, solar power stations, and the mixture of them. Currently, wind farms and solar power stations account for a combined generation share of 87.9% in Chinese NEPSs [3], while other types of NEPS are still in their initial development stages. In addition, China is propelling the reform of electricity marketization, encouraging new energy to enter the electricity spot market, and establishing a green certificate market to reflect the environmental value of renewable energy [4]. However, the uncertainty associated with the output of new energy power stations (NEPSs) poses a challenge to the security of power grid [5]. The introduction of adjustable resources such as energy storage can help NEPSs effectively resist uncertainty and reduce output fluctuation. Currently, the majority of energy storage facilities for NEPSs are constructed independently, giving rise to issues such as low resource utilization efficiency and limited capacity [6]. Given this context, the sharing economy theory is integrated with the energy storage industry. At present, there have been some research results on shared energy storage (SES), but the main research scenario is sharing between prosumers in communities [7-8], and few studies have discussed energy storage sharing between power stations. This paper focuses on the role of SES on the generation side and defines it as a centralized large-scale independent energy storage power station invested by a third party, which is mainly profitable by providing auxiliary services for NEPSs. SES can take advantage of the complementarity of discharge and charging demands between different new energy units, and fully improve the efficiency of resource utilization[9]. However, as a new energy storage mode, SES on the generation side still lacks the support of mature theory in cooperation mode and benefit allocation. Consequently, it is of vital importance to research the operation mode of new energy power stations cooperating with shared energy storage (NEPSs-SES) in spot market.

Currently, scholars have made certain research results in the cooperation of NEPSs and energy storage in the electricity market. These achievements primarily encompass the cooperation mode of NEPSs and energy storage, uncertain solutions, and the allocation of cooperation benefits. ISHIZAKI et al.[10] studies the affect of diverse energy storage penetration levels on social costs and personal profits when photovoltaic, energy storage and traditional energy participate in the day-ahead market (DAM) in the form of independent or cooperation. Dogan K et al.[11] and González-Garrido A et al.[12] construct a trading mechanism for new energy power joint energy storage to participate in multiple markets, proving the superiority of the new energy power-energy storage system. Mingtao M et al.[13] and Awnalisa W et al.[14] research collaboration mode of SES and NEPSs, and the conclusion shows that SES is more economical than independent energy storage. Tianhan Z et al.[15] propose a cooperation mechanism of SES assisting virtual power plants involving in energy and regulation markets, considering the capacity cost and battery degradation cost of SES. Overall, these studies do not take into account the combination of uncertainty in renewable energy output and multi-market interactions.

Faced with the uncertainty of NEPSs, scholars adopt methods such as stochastic optimization (SO), scenario generation (SG)[16] and robust optimization (RO)[17]. SO or SG need to assume that the output of new energy obeys a certain probability distribution, and generate lots of scenarios to simulate the real situation [18]. Simone P et al.[19] propose a stochastic optimization method for microgrid energy management system, which is integrated in a hierarchical model, based on two control layers and saving about 10% of fuel cost. Fei M et al.[20] use Latin hypercube sampling (LHS) to generate typical scenarios, and propose a day-ahead stochastic optimization model with the objective of minimum overall economic costs. However, both SO and

SG need certain probability distribution to generate scenarios, which is difficult to obtain accurately[21]. RO tends to consider the worst case, with no need for calculating the probability distribution or generate scenarios in advance [22]. Alvaro CG [23] proposed a two-stage RO model to address the issue of transmission network expansion planning, dividing the model into nested problems to solve. However, RO makes decisions based on worst-case scenarios, which infrequently occur in practice, and this high level of conservatism sacrifices a degree of economic efficiency [24].

In addition, because there are many players in the NEPSs-SES, it is essential to formulate a rational benefit allocation strategy to ensure the optimal operation of the alliance. Shapley value method is usually used for the need of profit distribution based on Cooperative Game Theory[25]. J. Zhang and W. Li.[26] summarize the current research status of revenue allocation method for multiple generators. Andrey C et al.[27] apply Shapley value and the Nucleolus to power construction project. Liwei J et al.[28] build a multi-factor distribution model to distribute the benefits of various agents in virtual power plants. Leilei Z et al.[30] propose an improved Shapley value method to solve the incentive problem between different entities of different cogeneration units. The above studies all distribute the income according to the contribution of players' marginal income in collaboration, but the application of these aforesaid methods in NEPSs-SES remains relatively underexplored. Meanwhile, the result of Shapley value method depends purely on the contribution of diverse players to cooperation revenues, ignoring characteristics and individual preferences of each player [31].

As to the analysis above, scholars have conducted extensive research on NEPSs and SES in the aspects of transaction mode, uncertainty analysis and operation model. Nevertheless, previous studies have not covered the following aspects: Firstly, some studies lack discussion on the interactive relationship between DAM, real-time market (RTM) and green certificate market; Secondly, when dealing with the uncertainty, most studies have certain challenges, including issues like the lack of objectivity in parameter estimation method, the complexity in solving SO model and the strong conservatism in RO model. Finally, there are few multi-factor benefit distribution systems for NEPSs-SES. Consequently, this paper puts forward a two-stage robust trading model of NEPSs-SES with improved uncertainty interval, and analyzes the trading results of DAM, RTM and green certificate market respectively. Then a benefit allocation strategy is designed based on the entropy weight modified Shapley value method, which further highlights the auxiliary role of SES. Table 1 intuitively summarizes the comparison between this paper and the existing work on NEPS and energy storage participation in the market. The primary innovations are as follows:

Table 1 The comparison between this paper and the existing work on NEPS and energy storage participation in the market

	Participator			multi-market	Benefits allocation	Uncertainty analysis
	WPP	PV	SES			
[7]	✓	✓	✓	×	×	Monte Carlo
[14]	×	✓	✓*	×	×	×
[15]	✓	✓	✓	✓	✓	×
[12]	✓	✓	✓*	✓	×	×
[28]	×	✓	✓	×	×	SO
[9]	✓	✓	✓	×	✓	×
[11]	×	✓	×*	✓	×	stochastic dynamic programming
This paper	✓	✓	✓	✓	✓	Improved two-stage Ro

“*” means that the energy storage does not exist as an entity.

(1) Designs a cooperative mode of NEPSs and SES participating in the power-green certificate market. In this paper, SES is divided into physical energy storage and virtual energy storage. In actual dispatching, if the charging and discharging demand of NEPSs coexists, the complementary part of charge and discharge can be directly connected to the grid through virtual energy storage without generating energy loss, and the deviation of the remaining part can be decreased by physical energy storage, so as to maximize energy utilization.

(2) Proposes a two-stage RO model with improved uncertainty interval, combining the advantages of SG and RO. In the DAM stage, based on the predicted output of NEPSs, the bid price and quantity are decided with the maximum income as the objective. In the RTM stage, taking into account the disparities between the actual generation of NEPSs and the bid quantity, the real-time trading plan is concocted with the objective of maximizing RTM incomes.

(3) Constructs an entropy weight modified Shapley value method considering contribution factors of risk, net income and investment. On the basis of the traditional Shapley value method distribution results, the above three factors are selected to get the improved distribution weight by entropy weight method, and the final benefit distribution ratio is determined by combination weight method. Eventually, the satisfaction degree of benefit allocation of each player is analyzed.

The remainder of this study is structured as follows. Section 2 introduces the trading framework of NEPSs-SES in the spot market. In section 3, a two-stage RO model is established, and the solution method is introduced. In section 4, an entropy weight modified Shapley value benefit allocation strategy is proposed, which considers factors of risk, net income and investment. In Section 5, a new energy base in Haixi, Qinghai Province, China is chosen for case study. Section 6 summarizes the contribution and conclusion of this study.

2 NEPSs-SES trading mode and uncertainty modeling

2.1 Trading mode

In this paper, a cooperative mode of NEPSs and SES participating in the power-green certificate market is proposed, as shown in Fig.1.

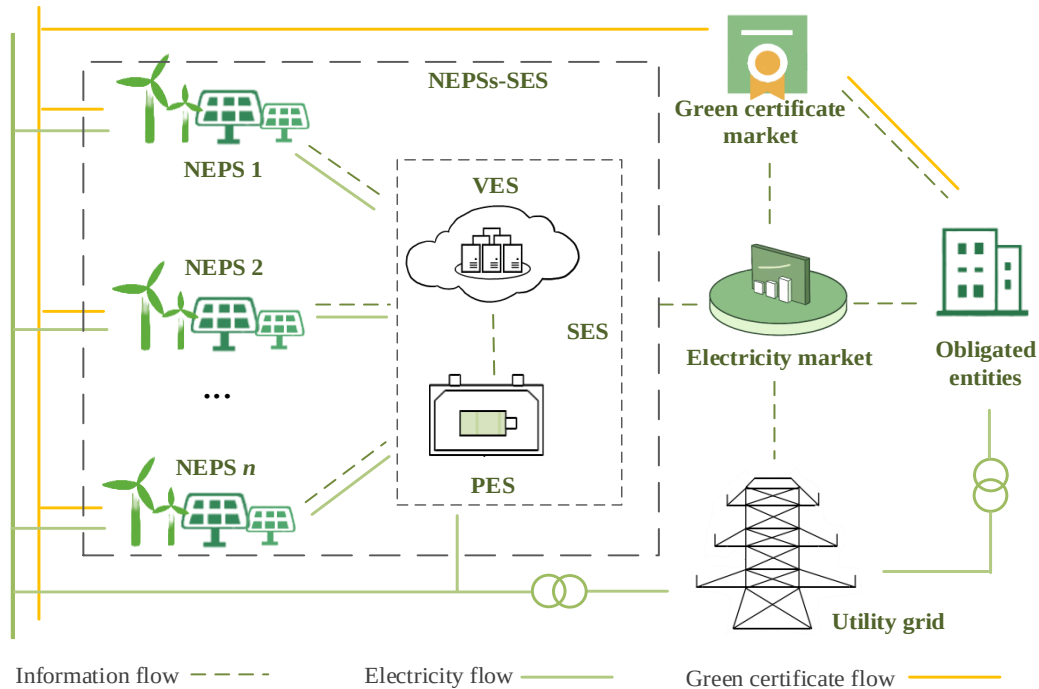


Fig. 1 Schematic diagram of NEPSs-SES participating in power-green certificate market

The alliance contains the following two subjects:

(1) New energy power stations (NEPSs). NEPSs is a collective term for multiple NEPS, which can be wind farm groups, photovoltaic power plant groups, or a combination of them. NEPSs can not only supply electricity in the spot market, but also trade green certificates in the green certificate market, thus reflecting the dual characteristics of economy and environment of green electricity. NEPSs will receive a green certificate for every megawatt hour of power produced. Green certificates can be sold through the green certificate subscription platform, and enterprises that fail to reach the renewable energy quota can choose to buy green certificates to offset the quota and decrease fines[32]. When there is a deviation between the actual output of NEPS and the bid quantity, NEPS can send a regulating demand signal to SES, thereby reducing the deviation power penalty.

(2) Shared energy storage (SES). SES includes physical energy storage (PES) and virtual energy storage (VES). When the SES receives regulating demand signals from multiple NEPSs simultaneously, it integrates the scheduling demands of all NEPSs to determine the output of its PES and VES. Firstly, the SES leverages VES to offset the complementary charge and discharge demands among NEPSs, significantly reducing the actual power deployment requirements. Secondly, SES calculates the remaining scheduling demands and utilizes PES power to fulfill them. As illustrated in Fig. 2, during actual scheduling, if there are concurrent charging and discharging demands from various NEPSs (where the charging demand of NEPS1 is e MW, the charging demand of NEPS2 is f MW, and the discharge demand of NEPS3 is g MW), assuming the total charging demand is less than the total discharge demand, the VES offsets the full charge demand and equivalent discharge demand ($e+f$ MW) at that time. Acting as an agent, VES then communicates the offset information to the power market. The remaining discharge demand ($g - (e+f)$ MW) is directly supplied to the grid from the PES output.

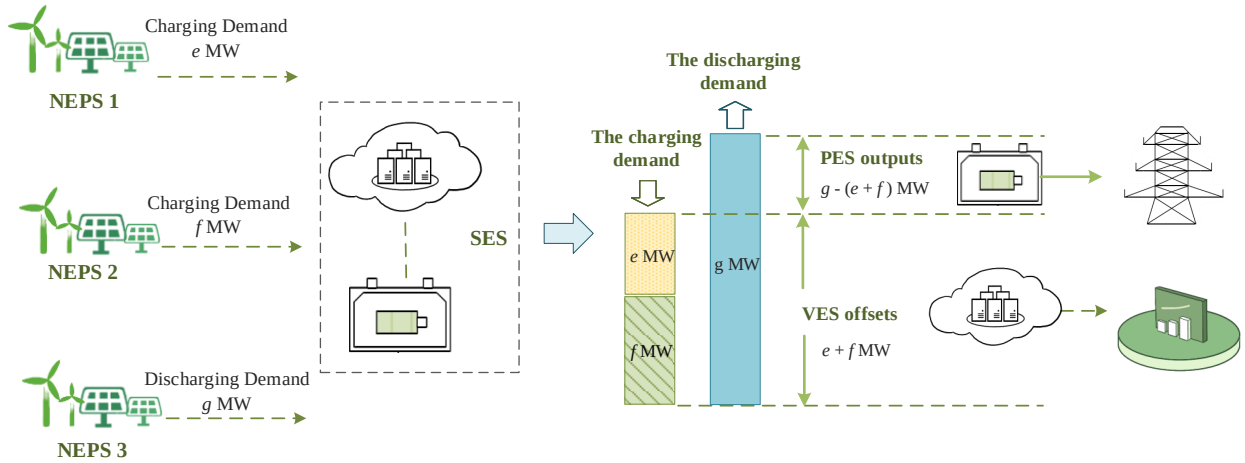


Fig. 2 Schematic diagram of VES-PES output

In this operating model, NEPS and SES function as equal partners without any hierarchical distinction. Each NEPS only communicates its regulating demands to SES, and there is no exchange of information between NEPSs. Moreover, there is no centralized control platform. Each NEPS is only aware of its own operational parameters, and SES is only informed about the adjustment requirements of NEPSs. In essence, the model employs decentralized scheduling where each NEPS pursues its own goal of profit maximization. SES, in turn, is solely responsible for fulfilling the regulating demands of NEPSs, and its benefits are derived through the allocation of alliance benefits. Compared with the independent energy storage mode (Fig.3(a)) or centralized dispatching mode (Fig.3(b)), the NEPSs-SES mode has obvious advantages:

In the independent energy storage mode, each NEPS pursues its individual profit maximization goal, treating physical energy storage as an integral component rather than a separate entity. Each NEPS participates separately in the power-green certificate market, utilizing only its own PES. Energy storages from other NEPSs can not be shared. When a NEPS generates excess electricity, and its energy storage capacity has reached the upper limit, with no option to utilize the energy storage of other NEPSs, the excess power goes to waste. In contrast, the shared energy storage in the NEPSs-SES model is considered as one entity within the alliance. Moreover, the NEPS in the proposed model can use the energy storage of other NEPSs to store excess power, and can also use VES to offset the opposite energy storage demands, so as to maximize the overall energy utilization.

In the centralized dispatching mode, NEPSs and SES are treated as an integrated system with an overall profit maximization objective. The centralized control platform receives detailed operational parameters from each NEPS and determines the charging and discharging actions of the energy storage. Moreover, in this mode, the centralized control platform participates in the power-green certificate market on behalf of the system and reports transaction information. Although energy storage is shared among NEPSs in this mode, large-scale centralized dispatching has some disadvantages such as privacy leakage and large amount of calculation in the optimization process, which challenges the secure operation of power grid. In contrast, the NEPSs-SES model is a cooperative group spontaneously formed by NEPS and SES. NEPSs and SES are regarded as independent entities and can independently engage in market transactions. NEPS only needs to communicate its scheduling requirements to SES, and no single agent possesses detailed operational information about the others. This mode is advantageous for minimizing the risk of information leakage, enhancing computational efficiency, and exhibiting good scalability.

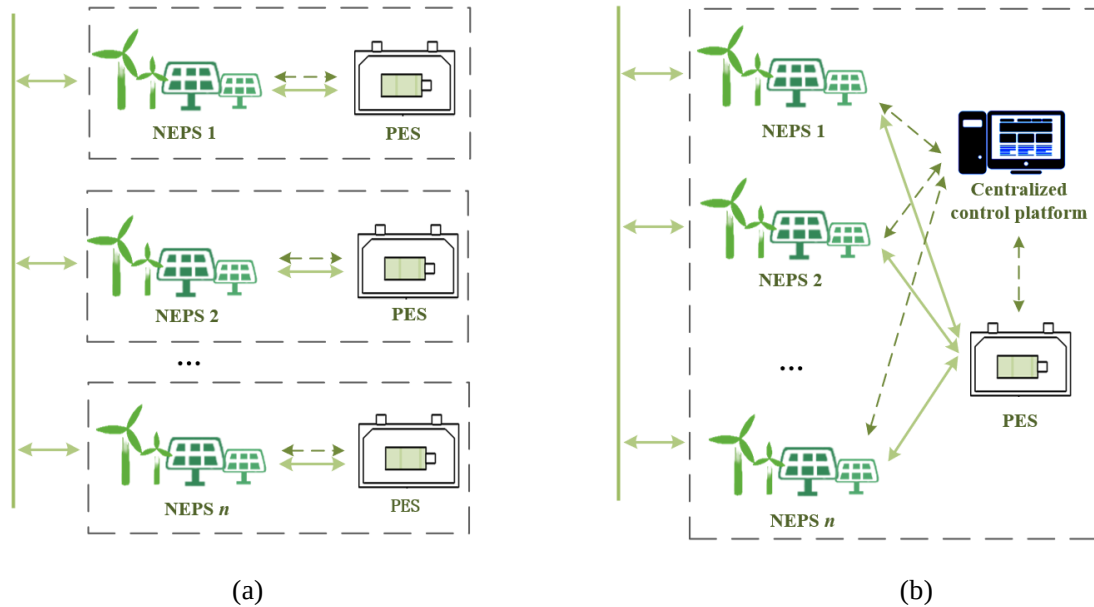


Fig. 3 Schematic diagram of independent energy storage mode and centralized dispatching mode

Additionally, the NEPSs-SES model proposed in this paper illustrates the relationship between the power market and the green certificate market, as depicted in Fig. 4.

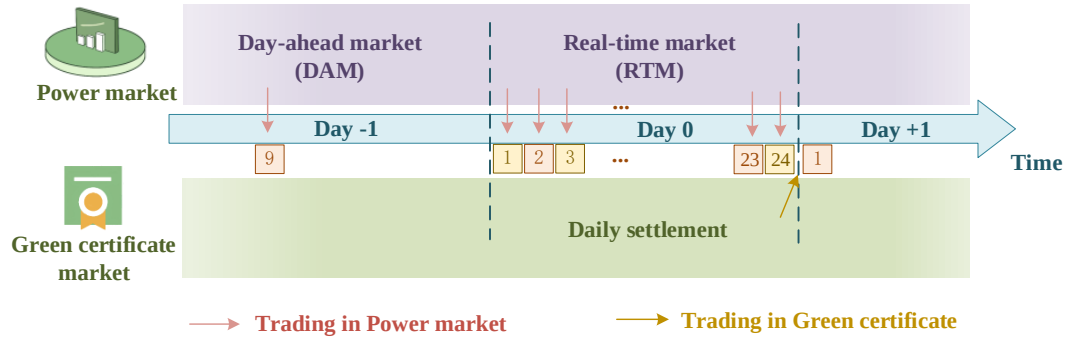


Fig. 4 Relationship between the power market and the green certificate market

In terms of electricity market: the electricity spot market comprises the day-ahead market (DAM), the intra-day market, and the real-time market (RTM). Given that the intra-day market's function overlaps with DAM and RTM, this paper concentrates on DAM and RTM. The transaction scenario is detailed as follows: at 9:00 am on the day (Day-1) prior to the formal operation day, NEPSs submit 24-hour transaction information for the next day (Day 0) to DAM (that is, DAM transaction frequency is once a day, with a cycle of 1 day), encompassing transaction price and quantity. On Day 0, armed with the DAM bid quantity and the actual output of Day 0, NEPSs mitigate the deviation by relaying adjustment demand information to SES. Deviations that SES cannot entirely rectify prompt NEPSs to engage in buying/selling power in RTM. RTM reporting occurs hourly, with transmitted information covering bidding price and quantity (that is, RTM transaction frequency is 24 times a day, with a cycle of 1 day).

In terms of the green certificate market: In China, the green certificate market operates as a highly flexible platform. Power generators have the freedom to choose their preferred timing for publishing sales information on the website. Buyers, in turn, can purchase certificates from the website if they find the price acceptable. Consequently, the time span for green certificate trading remains uncertain, varying from a single day to several weeks. In order to better reflect the coupling of the electricity-green certificate market, this paper divides the green certificate market into daily units, with trading once a day. Since the actual power generation for the entire day is only known after the day ends, it is set to report the green certificate information at the end of the 24th hour of Day 0 and directly calculate the revenue from its sale.

2.2 Uncertainty modeling

The current methods for addressing the uncertainty of renewable energy plant output are diverse, primarily falling into two categories: deterministic methods and data-driven methods. Deterministic methods, as shown in the introduction, contain SO, RO, and SG, addressing uncertainty by considering parameter variations or introducing randomness. Data-driven methods include machine learning and time series analysis, leveraging historical data or analyzing temporal correlations for prediction and decision-making [33,34]. Among these approaches, this paper opts for combining SG with RO as a means to handle uncertainty. Simulating wind and photovoltaic output scenarios through SG provides uncertainty intervals that better align with real-world conditions. This helps to overcome the oversimplification problem associated with the box uncertainty set in traditional RO. In the implementation of SG, to enhance sampling efficiency, this paper employs Latin Hypercube Sampling (LHS) based on the analysis of the NEPS output model and probability density functions (PDF). Compared to Monte Carlo simulation, LHS offers a more uniform coverage of the entire parameter space.

2.2.1 NEPSs output model

NEPSs are composed of wind farm groups or photovoltaic station clusters. Among them, the output of wind power plant (WPP) is mainly related to wind speed, and the photovoltaic (PV) output is mainly related to solar radiation.

(1) WPP output model. The mathematical relationship between the output of WPP and wind speed is as follows:

$$P_w = \begin{cases} 0, & 0 \leq v \leq v_{ct} \\ \frac{v - v_{ct}}{v_r - v_{ct}} P_r, & v_{ct} \leq v \leq v_r \\ P_r, & v_r \leq v \leq v_{co} \\ 0, & v_{co} \leq v \end{cases} \quad (1)$$

Where, P_w is the output power of WPP at time t ; v is the wind speed at any moment. v_{ct} , v_r , v_{co} are the cut-in speed, rated speed and cut-out speed, respectively. P_r is the rated power of WPP.

(2) PV output model. The mathematical relationship between the output of PV and solar radiation is as follows:

$$P_v(t) = \eta_{PV} \cdot S_{PV} \cdot \theta(t) \quad (2)$$

Where, $P_v(t)$ is the maximum output of PV at time t . η_{PV} and S_{PV} are the solar radiation efficiency and radiation area. $\theta(t)$ represents the solar radiation intensity at time t .

2.2.2 Uncertainty analysis and scenario generation

2.2.2.1 Uncertainty analysis

When using LHS to generate samples, the Cumulative Distribution Function (CDF) is used to ensure that the sampling is uniform across each dimension. Therefore, this paper takes suitable PDF to describe the uncertainty of WPP and PV respectively, and then converts the PDF to CDF.

(1) Uncertainty analysis of wind power

The uncertainty of WPP is mainly related to the randomness of wind speed, which is generally described by Weibull distribution[35]. Its function expression is as follows:

$$f(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \quad (3)$$

Where, c is the scale parameter. k is the shape parameter. c and k can be calculated from the sample.

(2) Uncertainty analysis of photoelectric

The uncertainty of PV is mainly related to the randomness of solar radiation intensity, which is generally described by Beta distribution[35]:

$$f(t) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \left(\frac{r_{PV}}{r_{PV}^{\max}}\right)^{\alpha-1} \left(1 - \frac{r_{PV}}{r_{PV}^{\max}}\right)^{\beta-1} \quad (4)$$

Where, r_{PV} is the solar irradiance; $r_{PV}^{\max}$ is the maximum solar irradiance. α and β are the shape parameter, which can be calculated from the sample.

2.2.2.2 Scenario generation

To address the randomness of new energy output, this paper proposes an improved LHS method to simulate the uncertainty of NEPSs output.

Although the traditional LHS method can achieve full coverage of the sample interval and can significantly reduce the aggregation phenomenon compared with Monte Carlo simulation, it does not consider the time series characteristics of the output of new energy in a day, resulting in all samples being obtained from the output model with the same shape parameters, which can not reflect the time characteristics of new energy power.

Therefore, based on the traditional LHS, this paper proposes an improved LHS method. First, divides the statistical data into different periods, and then constructs the cumulative distribution function (CDF) model with different shape parameters. Thus, the new energy output samples with daily characteristics can be obtained. Fig. 4 shows the flow chart of improved LHS method. And the specific method is as follows:

(1) Summarize all historical new energy power data by day and divide it into 24 time periods, ranging from 1h to 24h. Let any time period be $i, i=1,2,\dots,24$. Then the parameters of wind speed(k_i, c_i) and solar radiation(α_i, β_i) at time i can be calculated by the mean and standard deviation of samples.

(2) Construct PDF of wind speed and solar radiation in each period by Eqs. (3)-(4) according to the parameters, and derive the CDF $F_{k,i}$.

(3) Conduct LHS on $F_{k,i}$ for each period to generate several uncorrelated sample matrices. The sampling process is as follows:

Let the sampling scale be N , and divide the vertical axis of the above curve $F_{k,i}(X_{k,i})$ into N equally spaced intervals without overlapping. Since the dependent variable range of CDF is $[0,1]$, the length of each interval is $1/N$. Subsequently, complete random sampling is carried out in each interval $[(n-1)/N, n/N]$, and let the sampled ordinate value be $y_{kn,i}$. Put $y_{kn,i}$ into the inverse function of $F_{k,i}$, so the NTH sampled value of $X_{k,i}$ is:

$$x_{kn,i} = F_{k,i}^{-1}(y_{kn,i}) \quad (5)$$

Finally, K-means algorithm is used for scenario reduction, and the main steps can be seen in [36].

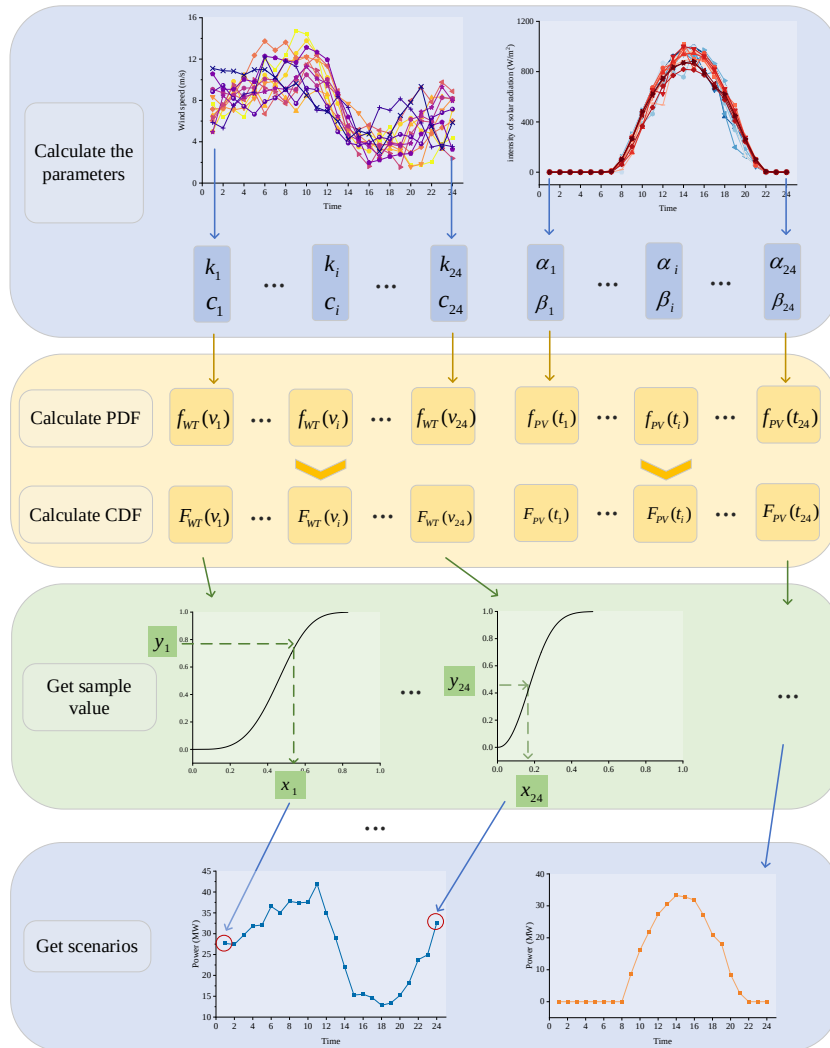


Fig. 5 Flow chart of improved LHS method

3 Day-ahead and real-time two-stage RO model

3.1 Two-stage trading framework

In this paper, the trading framework of NEPSs-SES alliance participating in the DAM and RTM is designed. In this framework, the trading includes the following two stages:

DAM stage: Members of NEPSs provide the trading center with the bid price and quantity for the next 24 hours according to the predicted power generation. By reason of the low marginal cost of the output, NEPSs can declare at a lower electricity price, so as to achieve the goal of winning the bid for all bid quantity, and finally obtain the power generation profit at the unified market clearing price.

RTM stage: NEPSs are informed of the bid quantity and the actual electricity generation. The alliance can invoke SES to make certain adjustments to deviations, thereby reducing the penalty costs associated with discrepancies. NEPS sends adjustment signals to SES, which aggregates all signals and then calls upon PES and VES to minimize deviations. Since the cooperative power of SES for each NEPS is a certain proportion of the NEPS power, SES will prioritize adjusting scheduling requirements within the specified cooperative power. It is important to note that due to the existence of VES, SES may still have scheduling space for PES after responding to all cooperative demands from NEPSs. In this case, SES will handle additional adjustment demands. If the remaining power of PES cannot meet all the additional demands, the scheduling quota of PES will be allocated according to the contractual ratio. In the absence of additional demands, SES will decide whether to purchase cheap electricity from the power market or sell electricity at a high price to the market based on the current electricity price.

The two-stage trading framework of NEPSs-SES collaborative participation in the DAM and RTM is shown in Fig.6.

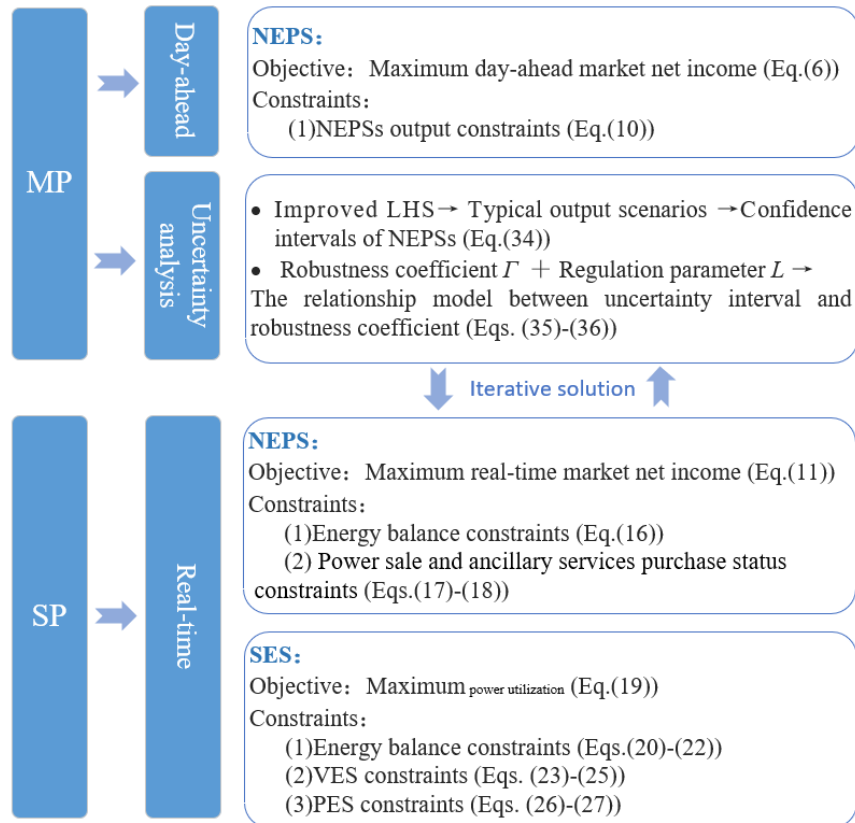


Fig.6 Block diagram of two-stage RO model construction.

3.2 Two-stage RO model

3.2.1 Traditional trading model

3.2.1.1 DAM transaction optimization model

In the NEPSs-SES model proposed in this paper, each NEPS has its own objective function and seeks to maximize its net return in DAM. NEPS forecasts the output of the next day, and combines the historical electricity price information to determine the bid quantity and price. The objective function in DAM of NEPS i is:

$$\max R_{net,i}^{ahead} = R_i^{ahead} - C_{RE,i}^{main} - C_{RE,i}^{de} \quad (6)$$

Where, $R_{net,i}^{ahead}$ is the net income of NEPS i in DAM. R_i^{ahead} is the income of NEPS i in DAM. $C_{RE,i}^{de}$ and $C_{RE,i}^{main}$ are the daily investment cost and daily maintenance cost of NEPS i , respectively.

$$R_i^{ahead} = \sum_{t=1}^T (p_t^{ahead} \cdot P_{t,i}^{RE}) \Delta t \quad (7)$$

$$C_{RE,i}^{main} = \frac{1}{365} \varepsilon_i P_i^{\max} \quad (8)$$

$$C_{RE,i}^{de} = \frac{1}{365} \frac{r(1+r)^{\gamma_{RE,i}}}{(1+r)^{\gamma_{RE,i}} - 1} de_{RE,i} P_i^{\max} \quad (9)$$

Where, T is set to 24. p_t^{ahead} is the clearing price of DAM at time t . $P_{t,i}^{RE}$ is the DAM bid quantity of the NEPS i at time t . Δt is the time interval. ε_i is the unit annual maintenance cost of the NEPS i . $de_{RE,i}$ is the unit annual investment cost of the NEPS i . $P_i^{\max}$ is the installed capacity of the NEPS i . r is the interest rate. $\gamma_{RE,i}$ is the depreciation life of the NEPS i .

Due to the constraint that the bid quantity of NEPS cannot exceed its forecasted output, the following constraint needs to be considered:

$$0 \leq P_{t,i}^{RE} \leq P_{t,i}^{RE0} \leq P_i^{\max} \quad (10)$$

Where, $P_{t,i}^{RE0}$ is the forecasted output of the NEPS i at time t .

SES remains inactive in DAM, so constraints related to SES do not need to be considered.

3.2.1.2 RTM transaction optimization model

Compared with the DAM, the RTM is more inclined to ensure the stability of power system operation. In the RTM, NEPSs are informed of the bid quantity and the market clearing price. At this time, the main objective is to reduce the deviation by SES and standby services to ensure the maximization of net income. Unlike in the DAM, both NEPS and SES have their own objective functions in RTM.

(1) NEPS.

The RTM objective of NEPS i is as follows:

$$\max R_{net,i}^{real} = R_{sell,i}^{real} + R_i^{green} - C_i^{DEVN} - C_{buy,i}^{real} \quad (11)$$

Where, $R_{net,i}^{real}$ is the net income of NEPS i in RTM. $R_{sell,i}^{real}$ is the income from electricity sale in RTM. R_i^{green} is the income from green certificates sale by NEPS i . C_i^{DEVN} is the deviation penalty cost. $C_{buy,i}^{real}$ is the ancillary service cost.

$$R_{sell,i}^{real} = \sum_{t=1}^T p_t^{real} P_{t,i}^{sell} \Delta t \quad (12)$$

$$R_i^{green} = \xi_{green} p_{green} \sum_i^N P_{t,i}^{RE1} \Delta t \quad (13)$$

Where, P_t^{real} is the clearing price of RTM at time t . $P_{t,i}^{sell}$ is the additional electricity sold by NEPS i in RTM. $P_{t,i}^{RE1}$ is the actual output of NEPS i at time t . ξ_{green} is the conversion coefficient of green certificate (1 MW green electricity is converted into 1 green certificate). p_{green} is the price of a green certificate.

$$C_i^{DEVN} = \sum_{t=1}^T (\delta_1 P_{t,i}^{sell} \Delta t + \delta_2 P_{t,i}^{buy} \Delta t) \quad (14)$$

$$C_{buy,i}^{real} = \sum_{t=1}^T p_t^{real} P_{t,i}^{buy} \Delta t \quad (15)$$

Where, $P_{t,i}^{buy}$ is the electricity purchased by NEPS i in RTM; δ_1 and δ_2 are the coefficient of positive and negative deviation penalty coefficient in RTM, respectively.

In the real-time stage, NEPS needs to consider constraints such as power balance, selling electricity, and purchasing ancillary services. Specifically, these are as follows:

a) Energy balance constraints

$$P_{t,i}^{RE1} + P_{SES_dis}^{t,i} + P_{t,i}^{buy} = P_{t,i}^{RE} + P_{SES_char}^{t,i} + P_{t,i}^{sell} \quad (16)$$

Where, $P_{SES_dis}^{t,i}$ and $P_{SES_char}^{t,i}$ are the discharge and charge requirements of NEPS i , respectively.

b) Power sale and ancillary services purchase status constraints

$$0 \leq P_{t,i}^{sell} \leq U_{t,i}^m P_i^{max} \quad (17)$$

$$0 \leq P_{t,i}^{buy} \leq (1 - U_{t,i}^m) P_i^{max} \quad (18)$$

Where, $U_{t,i}^m$ indicates the purchase and sale status of NEPS i .

(2) SES.

In the RTM stage, SES aims to maximize power utilization. Its objective function is as follows:

$$\max \sum_{t=1}^T (|P_{VES}^t| + |P_{PES}^t|) \quad (19)$$

Where, P_{VES}^t and P_{PES}^t are the outputs of VES and PES at time t . The specific calculation of VES and PES outputs can be obtained through the following equations:

$$P_{PES}^t = \sum_{i \in N} P_{SES_char}^{t,i} - \sum_{i \in N} P_{SES_dis}^{t,i} \quad (20)$$

$$P_{VES}^t = \begin{cases} \sum_{i \in N} P_{SES_char}^{t,i}, \sum_{i \in N} P_{SES_dis}^{t,i} < \sum_{i \in N} P_{SES_char}^{t,i} \\ \sum_{i \in N} P_{SES_dis}^{t,i}, \sum_{i \in N} P_{SES_dis}^{t,i} > \sum_{i \in N} P_{SES_char}^{t,i} \end{cases} \quad (21)$$

In fact, VES has equal positive and negative outputs at each time, so Eq. (21) calculates only one-directional output values. P_{PES}^t is a variable that can be positive or negative. When $P_{PES}^t < 0$, it indicates discharging; when $P_{PES}^t > 0$, it indicates charging. Therefore, for clearer expression, P_{PES}^t can be written in the following form:

$$P_{PES}^t = \begin{cases} P_{PES_char}^t, & P_{PES}^t > 0 \\ -P_{PES_dis}^t, & P_{PES}^t < 0 \end{cases} \quad (22)$$

Where, $P_{PES_char}^t$ and $P_{PES_dis}^t$ are the charging power and discharging power of PES at time t , respectively.

For SES, constraints need to be considered in both VES and PES aspects, as shown below:

a) VES constraints

As mentioned in Section 2.1, the charging and discharging behavior of VES does not produce energy waste, so the dynamic energy storage level of VES can be expressed as:

$$E_{VES}^{t+1} = E_{VES}^t + P_{VES}^t \Delta t \quad (23)$$

Where, E_{VES}^t and E_{VES}^{t+1} are the energy stored by VES at time t and time $t + 1$, respectively.

Because VES does not rely on physical equipment, its maximum charging and discharging power can be infinite in theory. For the convenience of expression, it is set as half of the maximum total power of NEPSs (because the VES will be invoked only when the positive and negative output deviation are offset):

$$P_{VES}^{\max} = \frac{1}{2} \sum_i^N P_i^{\max} \quad (24)$$

Where, $P_{VES}^{\max}$ is the maximum charging power and discharging power of VES.

In addition, since the charge and discharge of VES are equal at each time, the stored power does not change within a time period. For the convenience of expression and calculation, the VES power at time 0 is expressed as:

$$E_{VES}^0 = \sum_i^N P_i^{\max} \Delta t \quad (25)$$

b) PES constraints

PES needs to consider the charging and discharging efficiency during operation, so the dynamic energy storage level of PES can be expressed as:

$$E_{PES}^{t+1} = E_{PES}^t + (\lambda P_{PES_char}^t - \frac{1}{\lambda} P_{PES_dis}^t) \Delta t \quad (26)$$

Where, E_{PES}^t and E_{PES}^{t+1} are the energy stored by PES at time t and time $t + 1$, respectively.

In order to make the simulation results more representative of the general operating conditions of the NEPSs-SES alliance, the SES energy storage at time 0 and 24 should be at the same level, which can be expressed as:

$$E_{PES}^0 = E_{PES}^T \quad (27)$$

Additionally, physical energy storage needs to consider charging and discharging constraints as well as capacity constraints, as detailed in Appendix A.

3.2.2 Two-stage RO model

Given that the two-stage trading model discussed in this paper precisely aligns with the two stages of the RO theory and involves accounting for the impact of wind and solar uncertainties, the modeling approach adopted here is based on the two-stage RO theory. The mathematical model for traditional two-stage RO is expressed as follows:

$$\min_x a^T x + \max_{u \in U} \min_y b^T y \quad (28)$$

Where, x is the decision variable in the first stage; y is the decision variable in the second stage; u is the uncertainty variable; U is the uncertainty set.

In accordance with the analysis in Section 2 and 3, the NEPSs-SES model proposed in this paper considers each NEPS as having its own optimization objective, encompassing day-ahead and real-time stages. Consequently, each NEPS is treated as a complete two-stage robust optimization problem. It's important to note that all NEPS require information exchange with SES in the second stage. To conform to the general expression of two-stage RO, the first-stage objective function is negated to transform it into a minimization problem:

$$\min a^T x_i = -\max R_{net,i}^{ahead} \quad (29)$$

The objective function of the second stage in the proposed model seeks to maximize, hence it is merged as $\max_{u \in U, y} R_{net,i}^{real}$ instead of $\max_{u \in U} \max_y R_{net,i}^{real}$. Therefore, the abstract constraint model for the two-stage robust optimization of NEPS i is as follows:

$$\begin{cases} \min_{x_i} [a^T x_i + \max_{u \in U, y_i} b^T y_i] \\ s.t. Dy_i \geq d \\ Qx_i \geq q \\ Ky_i = k \\ Rx_i + Sy_i = 0 \\ Mx_i + Ly_i + Yu_i = 0 \end{cases} \quad (30)$$

Where, x_i and y_i are the decision variables in DAM and RTM, respectively. u_i is the uncertainty variable. And the specific expressions are:

$$\begin{cases} x_i = [P_{t,i}^{RE}]^T \\ y_i = [P_{t,i}^{buy}, P_{t,i}^{sell}, P_{SES_dis}^{t,i}, P_{SES_char}^{t,i}, U_{t,i}^m, U_{t,i}^s]^T \\ u_i = [P_{t,i}^{RE1}]^T \end{cases} \quad (31)$$

The above is the trading optimization model for a single NEPS. In reality, NEPSi can independently operate this model and interact with SES for information exchange. During simulation, variable (31) can be converted from a vector to a matrix, thus obtaining the operational results for multiple NEPS in one iteration:

$$\begin{matrix} x_1 & y_1 & u_1 \\ x = [\vdots]^T, y = [\vdots]^T, u = [\vdots]^T \\ x_N & y_N & u_N \end{matrix} \quad (32)$$

In this case, the entire model becomes:

$$\min_x [a^T x + \max_{u \in U, y} b^T y] \quad (33)$$

In addition, the traditional two-stage RO's uncertainty set U is a box uncertainty set, which cannot well reflect the true fluctuation range of renewable energy output. Therefore, this paper combines the SG method considering time series proposed in Section 2.2.2 to construct an improved uncertainty set. The main idea is to generate a large number of NEPS output scenarios through the time-based PDF of historical renewable energy output. The boundaries of the NEPS output at each moment in the scenarios are selected as the boundaries of the two-stage RO uncertainty set U . The specific steps are as follows:

1) Calculate the maximum fluctuation range of the output for NEPS i . Let $P_{t,j,i}^{RE1}$ be the output of NEPS i at time t under scenario j , then the maximum fluctuation range of $P_{t,j,i}^{RE1}$ is:

$$\begin{cases} \Delta P_{t,i}^{RE_up} = \max\{P_{t,j,i}^{RE1} - P_{t,i}^{RE0}, j \in J\} \\ \Delta P_{t,i}^{RE_down} = \max\{P_{t,i}^{RE0} - P_{t,j,i}^{RE1}, j \in J\} \end{cases} \quad (34)$$

Where, $\Delta P_{t,i}^{RE_up}$ and $\Delta P_{t,i}^{RE_down}$ are the upper and lower bounds of the fluctuation for NEPS i at time t .

2) Obtain the uncertainty set U . After calculating the fluctuation range, robust coefficient Γ is introduced to adjust the conservatism of the uncertainty set.

$$U = \begin{cases} P_t^{RE0} - \Gamma \cdot \Delta P_t^{RE} \leq \underline{P}_t^{RE0} \\ P_t^{RE0} + \Gamma \cdot \Delta P_t^{RE} \geq \overline{P}_t^{RE0} \end{cases} \quad (35)$$

Where, Γ is the robustness coefficient, which is used to adjust the conservative degree of the uncertainty set.

The larger the value, the higher the severity of the output fluctuation of the new energy unit, and the stronger the robustness of the scheduling result. $\bar{P}_t^{RE0}$ and $\underline{P}_t^{RE0}$ are the considered upper and lower bounds of NEPSs output, respectively.

As the output of NEPSs reaches the minimum value of U , it will face greater deviation penalty cost, which is more in accord with the meaning of “the extremely worst” scenario. Therefore, referring to the processing method of LIU Yixin et al. [21], the adjustment parameter L is introduced and Eq. (35) is rewritten into the following form:

$$U = \begin{cases} P_t^{RE1} = P_t^{RE0} - \Gamma \cdot B_t^{RE} \Delta P_t^{RE} \\ \sum_{t=1}^T B_t^{RE} \leq L \end{cases} \quad (36)$$

Where, B_t^{RE} is a binary variable.

3.3 Two-stage model solution

For each NEPS optimization model (30), the model can be equitably expressed as mixed integer linear programming problem (MILP), and the specific transformation process can be referred to Ref.[42]. However, due to the uncertainty of variables being represented in the form of intervals, the model cannot be directly solved. The Column and Constraint Generation algorithm (C&CG) [37] can solve traditional two-stage RO problems and obtain finite convergent solutions. The idea behind C&CG is to split problem (30) into a master problem (MP) and a subproblem (SP). By solving the SP and continually adding constraints to the MP, the objective function value of the MP increases, while the objective function value of the SP decreases. This process is repeated until the difference between the objective function values of the MP and SP narrows within a certain range.

However, C&CG requires the second stage to be a Linear Programming (LP) problem. If the second stage is an MILP problem, its objective function cannot be merged with the outer max through strong duality transformation. Although the second stage in this paper is an MILP problem, as described in Section 3.2, its objective function is a maximization optimization, and it can be directly merged with the outer max without the need for dual transformation. Therefore, the C&CG algorithm is adopted for solving.

By decomposing Eq. (30), the MP obtained at the k -th iteration of the two-stage robust model is as follows:

$$\left\{ \begin{array}{l} \min_x (a^T x + \theta) \\ s.t. \theta \geq b^T y_l \\ Dy_l \geq d \\ Qx \geq q \\ Ky_l = k \\ Rx + Sy_l = 0 \\ Mx + Ly_l + Yu_l^* = 0 \\ \forall l \leq k \end{array} \right. \quad (37)$$

Where, θ is the auxiliary variable of RTM stage income. l is the number of current iterations. y_l is the solution of the SP after the l -th iteration. u_l^* is the value of u in the extremely worst scenario after the l -th iteration.

The obtained SP is in the form of:

$$\left\{ \begin{array}{l} \max_{u,y} b^T y \\ \text{s.t.} \left\{ \begin{array}{l} Dy \geq d \\ Ky = k \\ Sy = -Rx \\ Ly = -Mx - Yu \end{array} \right. \end{array} \right. \quad (38)$$

After the above transformation, the two-stage RO model is decoupled into the MP Eq. (37) and the SP Eq. (38), both of which are mixed integer linear programming problems. Then the C&CG algorithm is used to solve the model, the process is as follows:

(1) Set the lower bound of the objective function as $LB = -\infty$ and the upper bound $UB = +\infty$.

(2) In the predicted worst-case scenario u^* , the MP Eq. (37) is solved, and the optimal solution (x_i^*, y_i, θ_i^*) is obtained. Take the obtained optimal solution as the new lower bound, i.e., $LB = a^T x_i^* + \theta_i^*$.

(3) Bring the obtained solution x_i^* of the MP into the SP, and then the optimal solution of SP $b^T y_i'$ is obtained. Taking the energy storage adjustment demand vector $\bar{P}_{SES}^t$ of SP into the SES optimization model, the optimal solutions $P_{PES}^{t,*}$ and $P_{VES}^{t,*}$, and the actual adjustment vector $\bar{P}_{SES}^{t,*}$ for NEPSs are obtained. Bringing $\bar{P}_{SES}^{t,*}$ back into the SP, updating the SP optimal solution $b^T y_i'$. Update the upper bound: $UB = \min\{UB, b^T y_i'\}$.

(4) Let the convergence threshold of the algorithm be ε , and if $|(UB-LB)/LB| \leq \varepsilon$, the calculation stops and the optimal solution (x_i^*, y_i^*) is returned. Otherwise let $l=l+1$, go to step 2.

It is worth noting that, in step 3), when solving the subproblem, NEPSs need to interact with the SES model. The solving process of the entire system (SES and multiple NEPSs) is illustrated in Fig. 7.

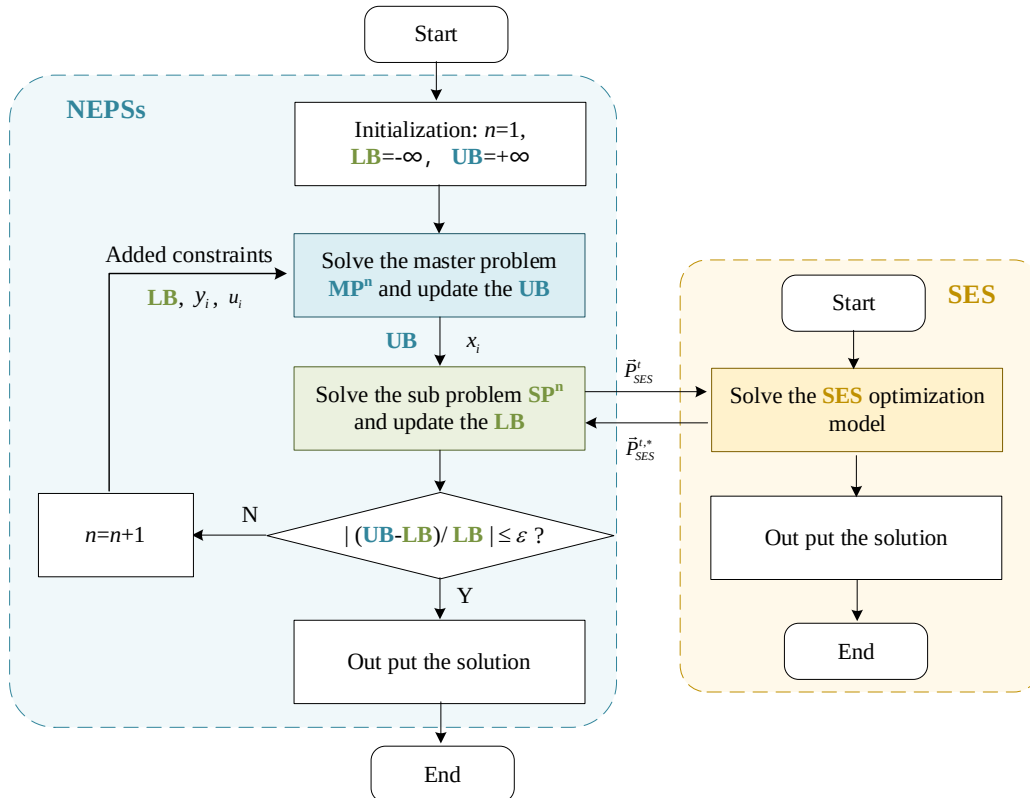


Fig. 7 Flow chart of solving two-stage RO

4 Benefit allocation strategy based on entropy weight modified Shapley value method

In the benefit allocation between NEPSs and SES, we propose an entropy weight modified Shapley value method (E-S method). The reason why Shapley value method is chosen is that it has the characteristics of

fairness and adaptability, and it is widely used in the field of electric power. Its fairness lies in considering each member's contribution to the overall cooperation. In the benefit allocation of NEPSs-SES, fairness is a key factor in ensuring that each player receives a reasonable share. Its adaptability lies in its calculation method, which is applicable to various types of cooperative games. In the benefit allocation of NEPSs-SES, this adaptability enables it to handle changing scenarios of energy output and demand.

However, it must be acknowledged that the Shapley value method has some limitations in dealing with uncertainty in factor weights[38]. Regardless of the weight of a factor, its contribution to the final collaborative benefit is considered the same. In reality, if SES has higher importance in this scenario, its weight should be given more consideration. Shapley value method does not account for this difference, and therefore, in certain situations, it may not accurately reflect the actual contributions of factors. To address this limitation, we introduce the entropy weight method. This approach is more flexible in dealing with uncertainty in factor weights, avoids subjective intervention, and is applicable to multi-criteria decision-making problems. The entropy weight method considers the measure of information [39], making it more accurate when dealing with multiple sources of information. Throughout the entire benefit distribution process, we leverage the objectivity of the entropy weight method and the fairness of the Shapley value method to ensure a fair and comprehensive assessment of the collaborative benefits for NEPSs and SES.

4.1 Entropy weight modified Shapley value benefit allocation model

As the Shapley value method and entropy weight method are widely used in the energy field, the fundamental theories are presented in Appendix A, with no further description in the main text. The basic idea of E-S method is as follows: first, calculate initial weights using the Shapley value method. Then, select multiple factors reflecting the contributions of alliance members and use the entropy weight method to calculate improved weights. Finally, balance the two methods using a combination weighting method to obtain the final weights and calculate the incremental gains for each member. The allocation framework of E-S method is illustrated in Fig. 8.

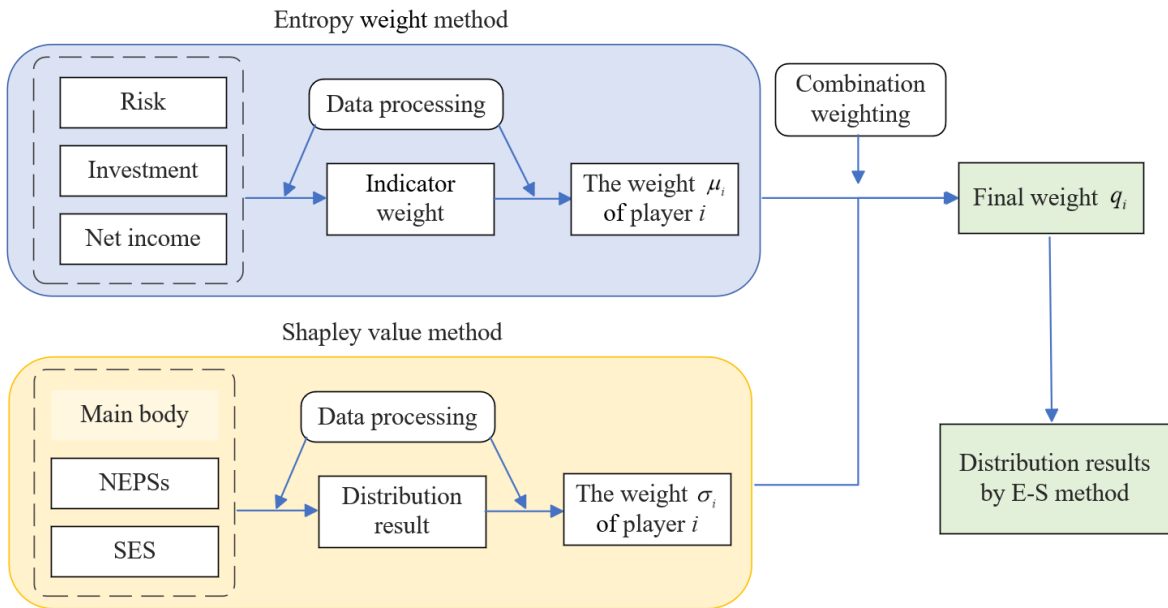


Fig. 8 Framework of E-S method

When choosing indicators for the entropy weight method, this study takes into account the influence of three factors—risk, investment, and net income—on profit distribution. To illustrate the interplay between these

two methods, results of Shapley value method are utilized in calculating the net income factor. The meanings and specific calculation methods of each factor are outlined below:

(1) Risk factor

Risk factor refer to the deviation of the actual output of alliance members due to the fluctuation of output. The specific calculation method is as follows:

$$fac_i^R = \sum_t^T \frac{|P_{t,i}^0 - P_{t,i}^1|}{P_{t,i}^1} \quad (39)$$

Where, $P_i^{\max}$ is the installed power of alliance member i . $P_{t,i}^0$ and $P_{t,i}^1$ are the predicted and actual output at time t , respectively. fac_i^R is the risk factor characteristic value of alliance member i .

Because the risk is inversely proportional to the benefit to be distributed, fac_i^1 should be maximized.

(2) Investment factor

Investment factor refers to the value of investment cost per unit power of alliance members. The specific calculation method is as follows:

$$fac_i^I = de_i \quad (40)$$

Where, fac_i^I the risk factor characteristic value of alliance member i .

(3) Net income factor

Net income factor refers to the contribution of alliance members to the alliance, which can be measured by distribution results of Shapley value. The specific calculation method is as follows:

$$fac_i^N = B_i \quad (41)$$

Where: fac_i^N is the net income factor characteristic value of alliance member i .

After separately calculating the allocation weights using Shapley value method and entropy weight method, it is necessary to combine these two weights using the combined weighting method. This ensures the relative balance of the weights, avoiding the dominance of a single factor. The specific procedure is outlined as follows:

$$q_i = \frac{\sqrt{\sigma_i \cdot \mu_i}}{\sum_i^N \sqrt{\sigma_i \cdot \mu_i}} \quad (42)$$

Where, q_i is the final weight calculated by E-S method; σ_i and μ_i are the weights calculated by Shapley value method and entropy weight method, respectively.

Finally, the weight is put into the following formula to obtain the incremental benefit distribution result of NEPSs-SES alliance:

$$B'_i = q_i \cdot (B - B^0) + B_i^0 \quad (43)$$

Where, B'_i is the benefit obtained by player i based on E-S method. B_i^0 is the benefit of the player i in the non-cooperative scenario; B^0 is the sum of the benefits of all players in the non-cooperative scenario.

At this point, we have obtained the final distribution results for the E-S method. Reviewing the entire process, the main steps of the E-S method are as follows:

- (1) Calculate the indicator weight W_j of three factors (risk, investment and net income), and according to W_j calculate the incremental benefit distribution weight μ_i of NEPSs and SES under entropy weight method.
- (2) Calculate the benefit allocation results of NEPSs and SES based on Shapley value, and then calculate the incremental benefit allocation weight σ_i of NEPSs and SES under Shapley value method.
- (3) Calculate the final assigned weight q_i of E-S method by combining μ_i and σ_i .

(4) Obtain the result B_i' of incremental benefit allocation.

4.2 Benefit allocation satisfaction evaluation

Under different distribution strategies, the benefit of players will be different. The higher the satisfaction of players, the higher the enthusiasm of participating in cooperation. In order to quantify the satisfaction of participants in the NEPSs-SES alliance with the results under different allocation strategies, a satisfaction evaluation model is constructed, as shown below:

$$G_j = \sum_{i=1}^N G_j^i = \sum_{i=1}^N (1 + \frac{B_i' - B_i^0}{B_i^0}) \quad (44)$$

Where, G_j is the overall satisfaction of the alliance under benefit allocation mode j ; G_j^i is the satisfaction of alliance player i under the benefit allocation mode j .

5 Case studies

This paper selects a new energy base in Haixi, Qinghai Province, China, to validate the feasibility and effectiveness of the proposed model and methods. Qinghai Province is a region in China with abundant resources, having a significant number of NEPSs. This makes the region highly representative in the development of renewable energy. Secondly, Qinghai Province was the first in China to propose a SES business model, providing historical data support for the collaborative model proposed in this paper. In addition, Qinghai Province has not yet initiated the electricity spot market, so simulating the performance of the NEPSs-SES model in the electricity spot market in advance holds certain reference value for the development of the new energy industry in Qinghai Province. We believe that through the case analysis of Qinghai Province, we can not only gain insights into the advantages of NEPSs and SES in a specific and unique context but also, to some extent, infer whether these advantages have broader applicability.

The overall idea of this section is as follows: by setting up five typical scenarios, the positive effects of energy storage and RO methods on alliance returns are verified. And the advantages of two-stage RO with improved uncertainty interval over conventional robustness are proved. By comparing the alliance satisfaction of basic Shapley value method and E-S method, the applicability of E-S method is proved. Finally, economic analysis is used to study the changes in the income of energy storage under different ways of participating in the market, so as to provide references for the commercial development of SES.

5.1 Parameter setting

In this new energy base, there are 5 NEPSs, namely 3 wind farms (W1, W2, W3) and 2 photovoltaic power plants (PV1, PV2). The installed capacities of wind farms are 100MW, 150MW and 200MW respectively. And the installed capacities of photovoltaic power plants are 100MW and 200MW respectively. All NEPSs are equipped with SES, and the power of SES is 5% of NEPS installed power. The selling price of green certificates refer to the average monthly price of the green certificates subscription platform, taking 45 ¥/unit. The geographical location of the base and other related parameters are shown in Fig. 9.

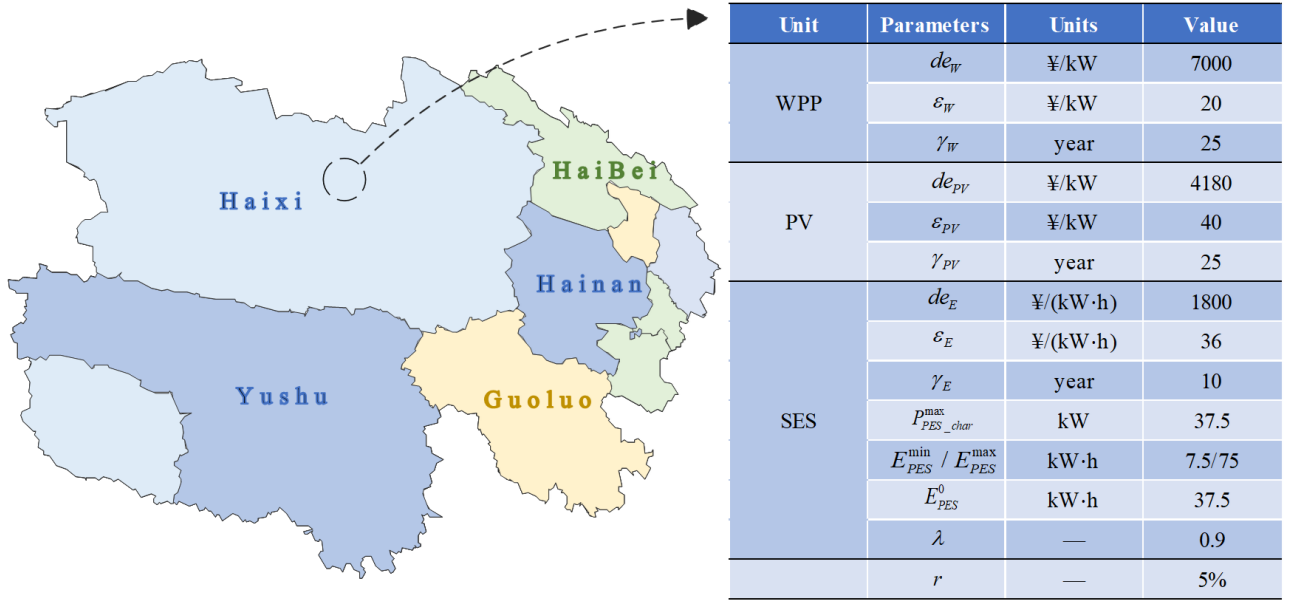


Fig. 9 Geographical location of the base and related parameters of the unit

According to the current green electricity trading mechanism in China's spot market, it is considered that all the bid quantity of NEPSs have won the bid, and the price is calculated according to the unified clearing electricity price in DAM. As there is no spot market in Qinghai Province at present, and both Qinghai Province and Gansu Province belong to the northwest provinces of China, the price trend of spot market in Gansu Province has strong reference significance for Qinghai Province, so the typical electricity price curve of spot market in Gansu Province is taken as the simulation power price, as shown in Fig. 10 for details. Set the coefficient δ_1 of positive Deviation penalty to 4 and the coefficient δ_2 of negative Deviation penalty to 0.25.

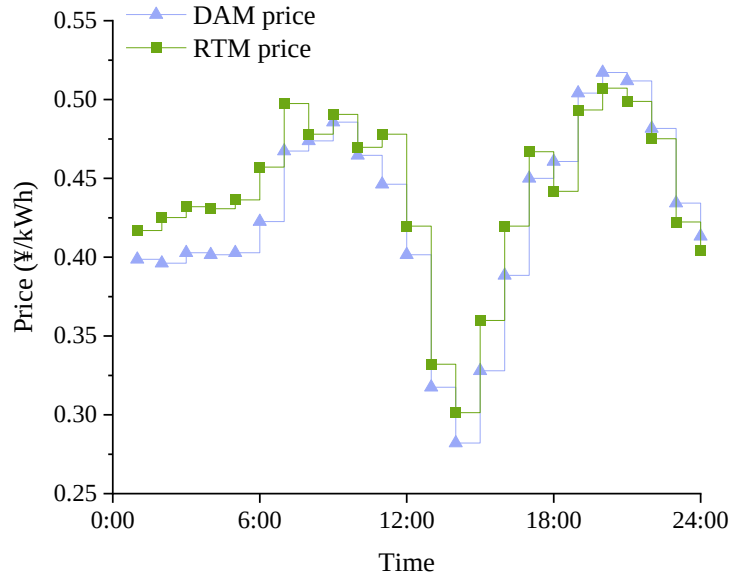


Fig. 10 Typical electricity price curve of Gansu spot market

Based on the scenario sampling method proposed in Section 2.2, 500 new energy output scenarios are generated by the improved LHS, and 10 typical new energy output scenarios are obtained by scenario reduction. The scenario with the highest probability is applied as predicted NEPSs outputs in day-ahead trading, and the scenario with the second-highest probability is applied as actual NEPSs outputs. After obtaining the uncertainty

set of the NEPSs output according to Eq.(35), the predicted/actual output curve of NEPSs can be drawn, as shown in Fig. 11 and Fig. 12. The solid line represents the actual output of each NEPS, and the shaded part with the same color as the solid line is the uncertainty set of the predicted output of each NEPS when the robustness coefficient Γ is 0.5. It can be seen that when Γ is less than 1, the predicted output range cannot completely cover the actual output curve.

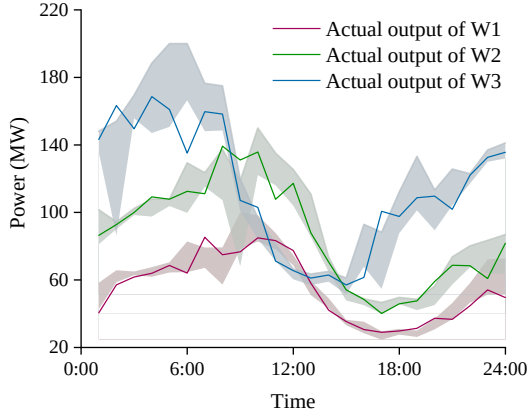


Fig. 11 Forecast/Actual output of WPP

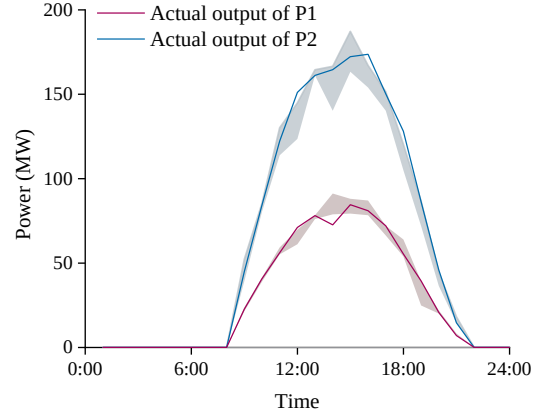


Fig. 12 Forecast/Actual output of PV

In order to prove the superiority of NEPSs-SES mode and the help of RO method to NEPSs-SES, the following four cases are established.

Case 1: Each NEPS participates in markets independently, regardless of the uncertainty of new energy output.

Case 2: Each NEPS participates in markets independently, and RO method is employed to address the uncertainty of NEPSs output.

Case 3: Each NEPS participates in markets by building its own energy storage and RO method is employed to address the uncertainty of NEPSs output. The energy storage scale of each NEPS is: The energy storage power is 5% of the installed power of NEPS, and the charging and discharging time is 2 hours. In addition, energy storage among different NEPS is not shared (as shown in Fig. 3(a)).

Case 4: NEPSs and SES participate in markets cooperatively and RO method is employed to address the uncertainty of NEPSs output. The energy storage scale of the whole NEPSs is: The energy storage power is 5% of the installed power of NEPSs, and the charging and discharging time is 2 hours. In addition, energy storage among different NEPS is shared (as shown in Fig. 1).

Case 5: NEPSs and SES participate in markets cooperatively and RO method is employed to address the uncertainty of NEPSs output. However, the alliance does not participate in the green certificate market.

It is worth noting that the total energy storage capacities in case 3 and case 4 are equal. The only difference is that one is not shared, while the other is shared. Therefore, it can better compare the auxiliary effect of SES on the participation of NEPSs in markets.

According to the above parameters, the two-stage RO model of NEPSs-SES is constructed by MATLAB R2020b. Subsequently, the commercial solver CPLEX12.10 and the YALMIP toolbox are invoked to solve the model. The processor of the simulation platform is Intel (R) Core (TM) i7-1165G7 CPU @ 2.80 GHz, and the RAM is 16.0 GB.

5.2 Comparison of results

5.2.1 Power transaction results

Firstly, to demonstrate the superiority of the two-stage RO with the improved uncertainty interval, the

result is compared with that obtained from the traditional two-stage RO. To control the range of uncertainty intervals, the maximum value of the traditional uncertainty interval width is set equal to the maximum value of the improved uncertainty interval width. The specific range of uncertainty intervals is detailed in Appendix B. The adjustment parameter L is set to 6. The comparison between traditional RO and improved RO for Case 2 to Case 5 is illustrated in Fig. 13. And "*" denotes the apices of the curves.

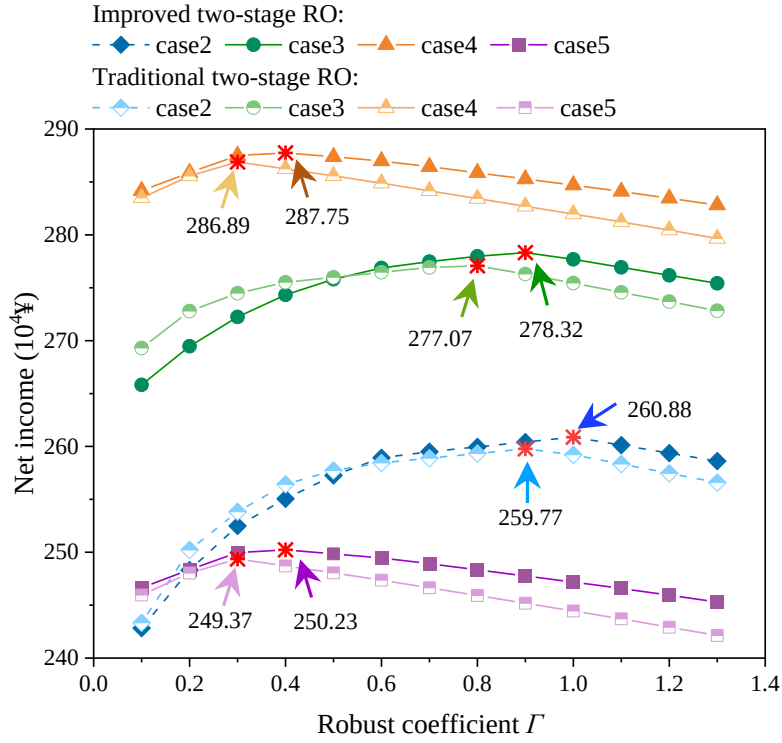


Fig. 13 Transaction results under different robust coefficients in cases 2 to 4

As shown in Fig. 13, it can be observed that as the robust coefficient increases, the objective function values of both optimization methods show a trend of initially increasing and then decreasing. It is worth noting that the curve shape of Case 4 is consistent with Case 5. This is because participation in the green certificate market and participation in the power market are mutually independent. Whether the alliance participates in the green certificate market does not affect its decision-making in the power market. The numerical value of Case 4 is higher than Case 5, and the difference represents the revenue from the green certificate market. Additionally, the optimal value of traditional RO has a smaller abscissa than improved RO, which is due to the overall slightly wider uncertainty interval of traditional RO. However, in either scenario, the optimal value of the improved RO is higher than that of traditional RO. Under the NEPSs-SES model advocated in this paper (Case 4), the net income of the improved method increases by 0.86×10^4 ¥, an increase of 0.3%. In summary, the calculation results of the improved RO are superior to traditional RO.

For the improved RO, comparing Case 2 to Case 4, we can see that with the addition of independent energy storage and SES, the alliance's ability to response to uncertainty increases, which makes the pole value shrink from 1 to 0.9, and then to 0.4, and the income increases twice, with the increase rates of 6.69% and 3.39% respectively. Through the comparison within cases and between different cases, it can be known that adding energy storage and using robust optimization methods can significantly improve the income of NEPSs in the spot market, and for different cases, appropriate robust coefficients should be selected to maximize the net income.

It is considered that the pole values in scenarios 2 to 5 are the true net income in these scenarios. And the transaction results and scheduling situation under different cases are shown in Table 2 and Fig. 14 respectively.

Table 2 Income under different cases /10⁴ ¥

Case		Income			Cost					Net income
		DAM	RTM	Green certificate	Investment	Operation	Power purchase	Negative deviation	Positive deviation	
1	NEPS1	58.46	1.78	5.92	13.61	0.55	3.85	15.41	0.44	32.3
	NEPS2	88.19	4.33	9.38	20.41	0.82	3.35	13.4	1.08	62.86
	NEPS3	120.61	4.57	12.32	27.21	1.1	6.83	27.32	1.14	73.89
	NEPS4	27.87	0.82	3.16	8.13	1.1	0.71	2.83	0.21	18.89
	NEPS5	57.06	3.19	6.75	16.25	2.19	0.28	1.13	0.8	46.34
Total Case1		352.19	14.69	37.52	85.61	5.75	15.02	60.07	3.67	234.28
2	NEPS1	52.55	5.19	5.92	13.61	0.55	1.26	5.04	1.3	41.9
	NEPS2	78.79	13.11	9.38	20.41	0.82	2.52	10.1	3.28	64.18
	NEPS3	107.81	14.17	12.32	27.21	1.1	2.87	11.48	3.54	88.1
	NEPS4	25.06	3.11	3.16	8.13	1.1	0.11	0.42	0.78	20.8
	NEPS5	51.89	8.4	6.75	16.25	2.19	0.12	0.48	2.1	45.89
Total Case2		316.09	43.98	37.52	85.61	5.75	6.87	27.49	11.00	260.88
3	NEPS1	53.11	3.58	5.92	14.25	0.65	0.4	1	0.76	45.56
	NEPS2	79.68	10.2	9.38	21.37	0.97	0.79	3.17	2.41	70.55
	NEPS3	109.03	10.31	12.32	28.49	1.29	0.72	2.62	2.45	96.09
	NEPS4	25.31	2.84	3.16	8.76	1.19	0.06	0	0.56	20.73
	NEPS5	52.35	7.84	6.75	17.53	2.39	0	0	1.62	45.39
Total Case3		319.48	34.77	37.52	90.40	6.49	1.97	6.79	7.79	278.32
Total Case4		340.60	15.64	37.52	90.40	6.49	4.23	1.13	3.77	287.75
Total Case5		340.60	15.64	0	90.40	6.49	4.23	1.13	3.77	250.23

In Table 2, the NEPS benefits for Case1 to 3 are detailed. It is important to note that the detailed benefits of Case3 refer to the benefits of NEPS cooperating with SES, not the benefits of NEPS themselves. The details of Case4-5 are not listed because they need to be obtained through the distribution of benefits.

According to Table 2, the comparison between Case 1 and Case 2 shows that the negative deviation penalty of NEPSs can be significantly reduced by 54.24% by using robust optimization. At the same time, the bid quantity in DAM of Case 2 is more conservative, which makes the revenue of power sales in DAM decline. The power sales increase in the RTM stage, and the positive deviation penalty increases. On the whole, the use of robust optimization makes the net income of NEPS increase by 26.60×10^4 ¥, an increase of 11.35% under Case 2. Comparing Case 2 to 3, it shows that although the addition of energy storage increases the investment cost and operating cost of the alliance by 5.60% and 12.87% respectively, the negative deviation penalty can be significantly reduced after the addition of energy storage. Taken together, the income in Case 3 is 17.44×10^4 ¥ higher than that in Case 2, with an increase of 6.69%. Comparing Case 3 to 4, it can be seen that SES makes the alliance have stronger anti-risk ability, and the bid quantity in DAM is greater than that in Case 3. In Case 4, SES is used to improve the efficiency of resource utilization. In consequence, the deviation penalty in Case 4 decreased by 9.68×10^4 ¥, and the net income increased by 9.43×10^4 ¥, an increase of 3.39%.

Comparing Case 5 to 4, we can see the important role of the green certificate market. After losing the green certificate market revenue, the revenue in Case 5 decreased by 13% compared with Case 4. In addition, although the typical daily electricity price selected in the current case is at a regular level, there will be low electricity market prices on some days during the year, resulting in uncertainty in NEPSs revenue. Participation in the green certificate market enables NEPSs to diversify its revenue streams and reduce its sensitivity to

fluctuations in the electricity market, helping to stabilize NEPSs' financial position.

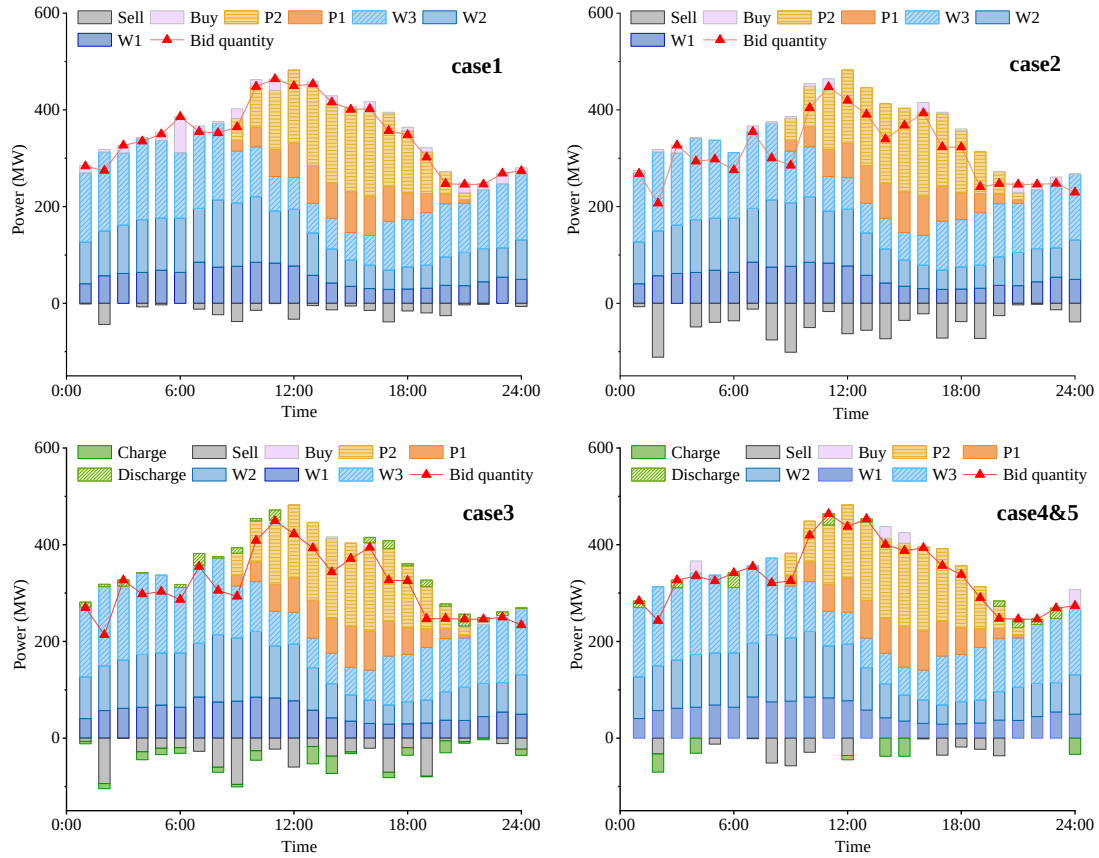


Fig. 14 Alliance scheduling in different cases

In Fig.14, "buy" refers to the power of auxiliary services purchased by the alliance from the market in order to balance the negative deviation. "sell" refers to the power the alliance sells to the market in order to balance the positive deviation. According to Fig. 14, the comparison between Case 1 to 2 shows that the use of robust optimization makes the bid quantity of Case 2 decrease in day-ahead stage, and leads to the increase of electricity sales in real-time stage. In addition, both Case 1 (7h, 9h et) and Case 2 (16h, 21h et) have the situation that electricity purchases and sales occur at the same time, which is because the NEPSs cannot cooperate with each other, resulting in the inability to carry out complementary charge and discharge. Comparing Case 2 to 3, it shows that the addition of energy storage makes it no longer necessary for the alliance to balance its own power generation deviation by buying and selling electricity for some time periods, such as 20h; or significantly reduce the deviation of electricity, such as 13h, 14h. In addition, it can be seen that in Case 3, there is coexistence of charge and discharge of energy storage at the same time, such as 2h, 6h, etc., which leads to the underutilization of resources. Comparing Case 3 to 4, it shows that the addition of SES in Case 4 increases the DAM bid quantity for most of the period. At the same time, due to the joint action of VES and PES, there is no coexistence of charge and discharge in the same period of time in Case 4, and the real-time deviation power is greatly reduced compared with Case 3.

In order to further verify the advantages of SES, the working states of energy storage in Case 3 and Case 4 are analyzed in detail, as shown in Fig. 15.

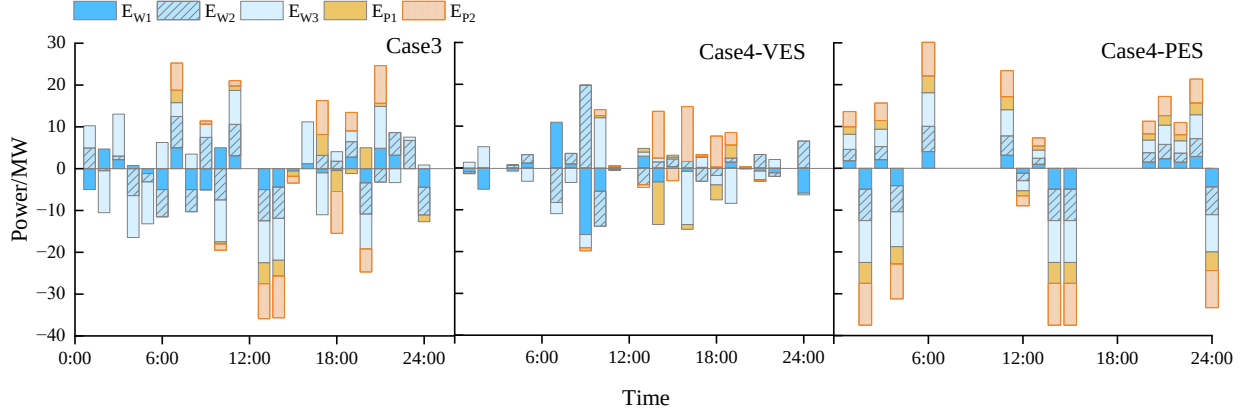


Fig. 15 Comparison of energy storage operation in Cases 3 and Cases 4

According to Fig. 15, in Case 3, in order to reduce the deviation penalty, the state of energy storage charging and discharging among different NEPSs at the same time is opposite, resulting in unnecessary waste of energy. Although energy storage at some time can chase the profit of electricity price difference, charging in the low price period (13h—14h) and discharging in the peak period (19h, 21h), the regulation function of energy storage is not maximized due to the different charging and discharging conditions among different NEPSs.

In case 4, on the virtual energy storage platform, the demand for charging and discharging of SES of each alliance member is offset at most times in a scheduling cycle. From the point of output power, the maximum power of VES can reach 52.7% of the maximum power of PES. From the point of call time, the call time of VES is more than that of PES. The use of VES greatly reduces the operating loss and cost caused by SES. At the same time, the capacity demand of SES can be reduced if the charging and discharging demand of energy storage among members is offset. In the planning and construction stage, the alliance can choose energy storage with smaller capacity to reduce investment costs.

To sum up, adding energy storage and using robust optimization methods can significantly improve the income of NEPS in the spot market, and sharing energy storage can get higher profits than not sharing it.

In order to prove the scientificity and applicability of the model proposed in this paper, the results of some published papers and real projects are compared with the results of this paper. Therefore, this paper considers two indicators of net income per kwh (NIPK) and internal rate of return (IRR), and chooses one of them for comparison according to the actual situation. The specific expressions of the indicators are shown as follows:

(1) NIPK calculation model.

$$R_{NIPK} = \frac{\sum_i (R_{net,i}^{ahead} + R_{net,i}^{real})}{\sum_i \sum_t P_{t,i}^{RE1}} \quad (45)$$

(2) IRR calculation model.

$$\sum_{n=0}^N C_n (1 + r_{IRR})^{-n} = \sum_{n=0}^N R_n (1 + r_{IRR})^{-n} \quad (46)$$

Where, n is the year; N is the life cycle; r_{IRR} is the internal rate of return; C_n is the cash outflow in the year n ; R_n is the cash flow in the year n .

In addition, not every day of NEPS output can be at the level of a typical day in this case, so the IRR is calculated on 210 days of annual generation. The comparison results are shown in the Table 3. (The results of this paper are the results of case4).

Table 3 Compare with published results or real projects

	Published results				Real projects	This paper
	[46]	[43]	[44]	[45]	[47]	
NIPK (¥/kWh)	0.27	0.88	0.73	-	-	0.35
IRR (%)	-	-	-	10.87%	6%-7%	10.70%

It is worth noting that Ref. [43] and [44] do not consider the investment cost of new energy generators, so the NIPK is higher than the normal value; In addition, the settlement currency of Ref. [43] and [44] is USD, which may also be one of the reasons for the high results given the exchange rate between USD and CNY. In general, the results of this paper are within the reasonable range, and the economic benefits are excellent.

5.2.2 Benefit allocation results

According to the analysis in Section 5.2.1, when the robustness coefficient I' is set to 0.4, the alliance benefit reaches the optimal value, so the benefit allocation in this section is based on the alliance benefit when I' is set to 0.4. The net income in the independent operation scenario and the net income allocated based on Shapley value in the cooperation scenario, are shown in Table 4. Among them, the revenue sources of SES in the independent operation scenario are the peak-valley price difference and the peak-shaving service of 0.2/kWh.

Table 4 Income of players in case of independent operation and case of basic Shapley value / (10⁴¥)

Players	Independent operation	Basic Shapley value method
NEPSs	260.877	275.985
SES	-3.347	11.761

According to the evaluation factors selected in Section 4.2, the characteristics of alliance members are shown in Table 5.

Table 5 Characteristics of alliance members

Players	Risk factor	Investment factor	Net income factor
NEPSs	0.00	0.11	275.98
SES	665.80	0.13	11.76

According to the model described in Chapter 4, the incremental benefit distribution weight σ_i of Shapley value method is 0.5 and 0.5 respectively. The incremental benefit distribution weight μ_i of entropy weight method is 0.413 and 0.587 respectively. According to Eq. (42), the incremental benefit distribution weight q_i of entropy weight modified Shapley value method is 0.456 and 0.544 respectively.

Due to the addition of SES, the ability of NEPSs to deal with uncertain risks is improved. NEPSs can bid more electricity in DAM to avoid a large amount of electricity that cannot be quickly consumed in RTM.

In order to highlight the positive effect of SES on the consumption of green electricity, two benefit allocation modes of green certificate based on E-S method are proposed:

Distribution mode 1: The green certificate income is directly obtained by NEPSs and does not participate in the distribution.

Distribution mode 2: The corresponding green certificate revenue which is generated because the increase of the bid quantity in DAM due to the addition of SES is regarded as incremental revenue, and participates in the distribution.

The results of the two distribution methods are shown in Table 6.

Table 6 Results of incremental benefit allocation

	E-S method: Distribution mode 1		E-S method: Distribution mode 2	
	NEPSs	SES	NEPSs	SES
Result of E-S method	274.659	13.087	273.182	14.564

Unit: 10⁴¥

Increase or decrease compared with non-cooperation	13.782	16.434	12.305	17.911
Increase or decrease compared with basic Shapley value method	-1.326	1.326	-2.803	2.803

According to Table 4, under the distribution mode 1, compared with basic Shapley value, the income of SES increased by 1.326×10^4 ¥. Under the distribution mode 2, compared with basic Shapley value, the income of SES increased by 2.803×10^4 ¥, 1.477×10^4 ¥ more than that of the mode 1. Combined with Fig. 16, it can be seen that the overall satisfaction of distribution method 2 is the highest, so it is the optimal allocation strategy, which further reflects the important role of SES in smoothing the fluctuation of new energy output and improving economic benefits.

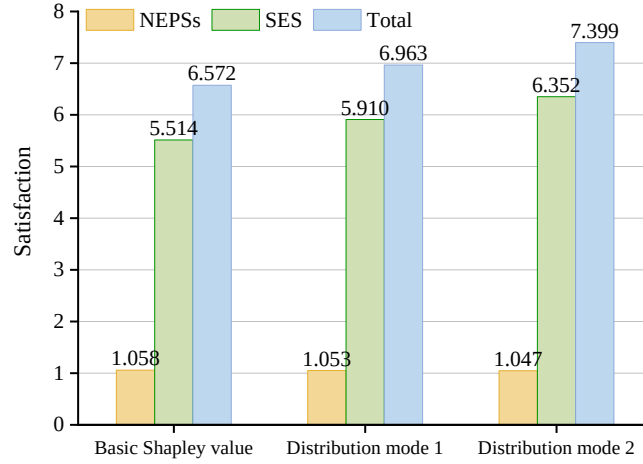


Fig. 16 Satisfaction degree of distribution results by E-S method

In addition, although the income of NEPSs decline, it is still higher than that of NEPSs participating in the spot market alone. Therefore, the proposed method conforms to the basic constraints, and the allocation strategy of E-S method has certain feasibility.

Further, the distribution results of each NEPS are analyzed. The characteristics of entropy weight method are shown in Appendix B. The calculation results of NEPSs weight are shown in Table 7.

Table 7 The results of NEPSs weight

	Distribution mode 1			Distribution mode 2		
	μ_i	σ_i	q_i	μ_i	σ_i	q_i
NEPS1	0.1476	0.1576	0.1601	0.1445	0.1593	0.1573
NEPS2	0.2441	0.4330	0.3413	0.2493	0.4187	0.3351
NEPS3	0.2963	0.3200	0.3233	0.2928	0.3062	0.3105
NEPS4	0.1035	0.0330	0.0614	0.1033	0.0461	0.0716
NEPS5	0.2086	0.0564	0.1139	0.2101	0.0697	0.1255

As can be seen from Table 7, if only Shapley value method weights are considered, then the wind farm (NEPS1-NEPS3) will have an advantage. This is due to the fact that Shapley value method focuses more on the revenue contribution of members to the alliance. Photovoltaic power plants only have a 10-12h output period in a day, so wind farms of the same scale generate more power than photovoltaic power plants and earn more. From the perspective of entropy weight method, photovoltaic power plants have made significant contributions to risk reduction and investment. Combining these two methods, the weight of E-S method is more persuasive. Compared with mode 1, the change of green certificate income distribution makes the allocation weight of NEPS2 and NEPS3 decrease. This is because these two NEPSs have more bid quantity in the DTM due to the

addition of SES and more green certificate earnings are distributed to SES. In general, members with less volatility and larger power generation will occupy a larger share of incremental benefit distribution.

The final benefit distribution result within NEPSs is shown in Fig. 17:

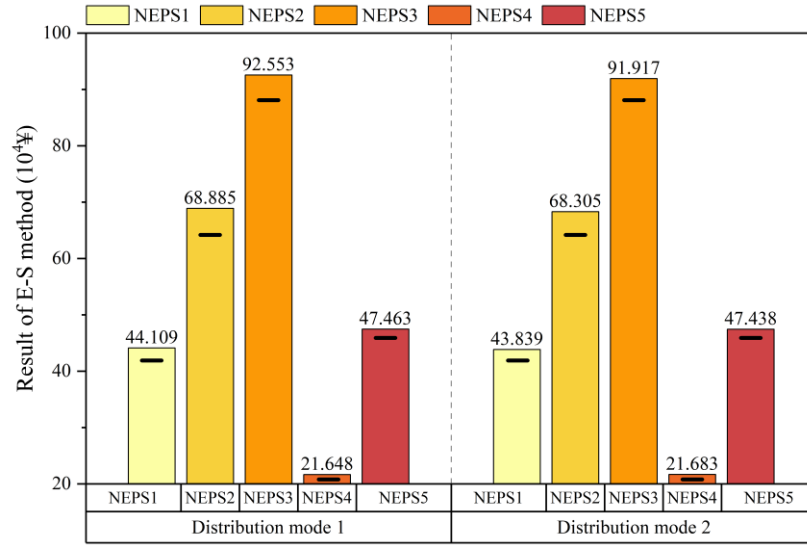


Fig. 17 The final benefit distribution result within NEPSs

In the Fig. 17, "—" represents the revenue under the scenario where NEPSs do not cooperate (i.e. the revenue under Case2).

5.2.3 A larger test system

Further, to demonstrate the applicability of the model in a larger system, we added five new NEPSs members to the alliance. Among them, there are three wind farms (W4, W5, W6), rated power of 150MW, 200MW, 250MW. And two photovoltaic power plants (P3, P4), rated power of 250MW, 200MW. The output curves and uncertainty intervals are shown in Fig. 18. And the comparison between its net income and that obtained by traditional RO is shown in Fig. 19.

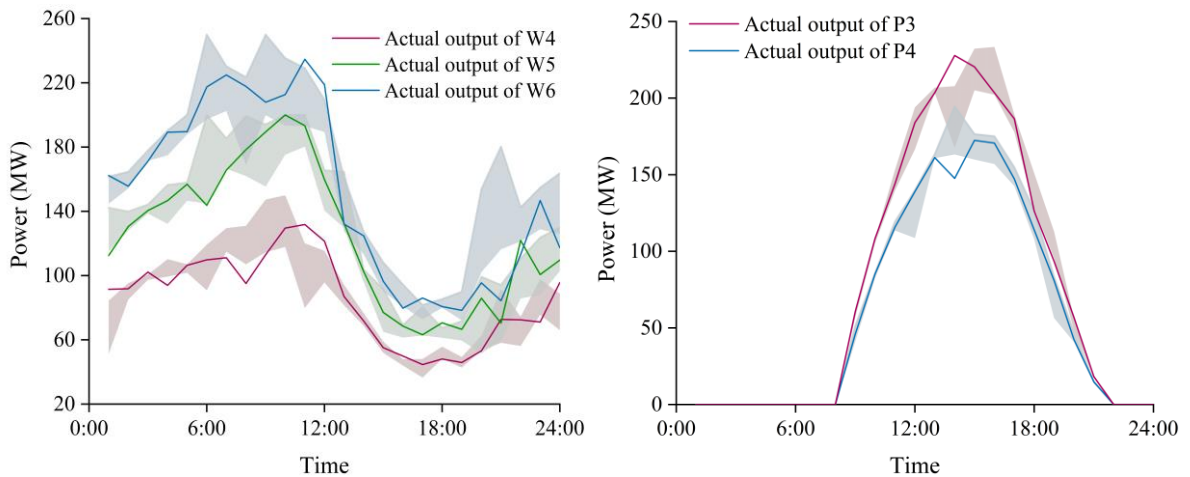


Fig. 18 Forecast/Actual output of NEPS 6-10

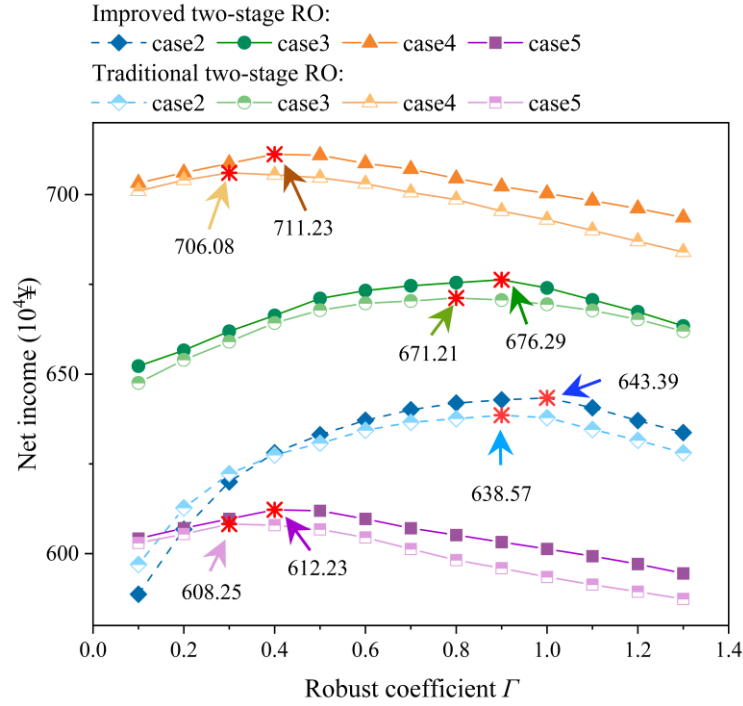


Fig. 19 Forecast/Actual output of NEPS 6-10

As can be seen from Figure 19, when the system is expanded to include 10 NEPS, the cooperation model and the improved optimization model proposed in this paper are still applicable. Among them, Case4 had the highest net income of 711.2×10^4 ¥. This suggests that the NEPSs-SES cooperation model is suitable for larger systems. Compared with improved RO and traditional RO, the optimal return of improved RO is higher. This shows that improved RO is also suitable for larger systems.

5.3 Economic analysis of energy storage

In the previous analysis, we delved into the benefits of NEPSs-SES participation in the markets and explored the potential impact of the partnership on NEPS-SES. In order to better understand SES's performance in the electricity market, we will further compare the effect of SES's participation in the electricity market through other means. Through this comparison, we aim to reveal the economic benefits and potential challenges of different decision paths, thereby providing deeper insight into sustainable energy management.

At present, SES can participate in electricity energy trading and ancillary services trading as an independent entity, or sign a lease contract with NEPSs to directly provide auxiliary services. The representative power stations of the former include Shandong independent energy storage power station [40] and Minhang independent energy storage power station [41] in Qinghai Province. Among them, the income sources of Shandong independent energy storage power station are mainly the peak-valley price difference obtained in the electricity spot market and the capacity compensation fee. The income sources of Minhang independent energy storage power station are mainly peak shaving service and subsidy income. Therefore, to verify the economic viability of the SES mode proposed in this paper, three additional extension cases are set for comparative analysis, using Case 4 introduced in Section 5.1 as the basis:

Case 4-1: SES participates in markets as an independent entity, and the income sources are the peak-valley price difference and capacity compensation fee.

Case 4-2: SES participates in markets as an independent entity, and the income sources are peak shaving

service and subsidy income.

Case 4-3: SES signs a lease contract with NEPSs.

The energy storage capacity is the same as Section 5.1, which is 37.5 MW/75 MWh. The power consumption of Case 4-1 and Case 4-2 is calculated by fully charging for 300 times throughout the year. The specific formula of energy storage costs and benefits is shown in Appendix B.

Two typical indicators, IRR and net present value (NPV), are selected as evaluation indicators to analyze the results. The IRR model is in Appendix B NPV model is as follows:

(1) IRR calculation model.

$$\sum_{n=0}^N C_n (1 + r_{IRR})^{-n} = \sum_{n=0}^N R_n (1 + r_{IRR})^{-n} \quad (47)$$

Where, n is the year; N is the life cycle; r_{IRR} is the internal rate of return; C_n is the cash outflow in the year n ; R_n is the cash flow in the year n .

(2) NPV calculation model.

$$NPV = \sum_{n=0}^N (R_n - C_n)(1 + i)^{-n} \quad (48)$$

Where: i is the benchmark yield.

Fig. 20 shows the variation of IRR in different cases, and Fig. 21 shows the variation of NPV in different cases when the discount rate is 5%. In general, it is considered that if the IRR reaches more than 8%, the project has investment value. If the IRR exceeds 10%, the project economy is excellent.

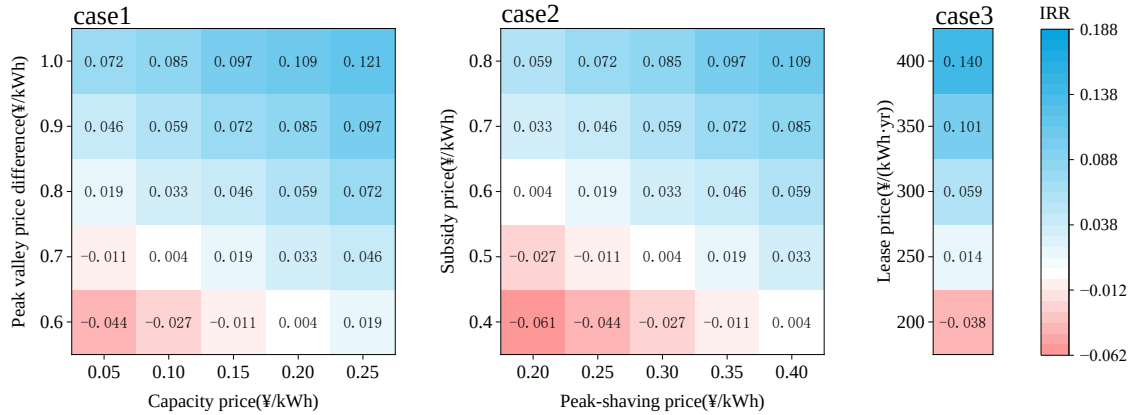


Fig. 20 Hot map of IRR in different cases

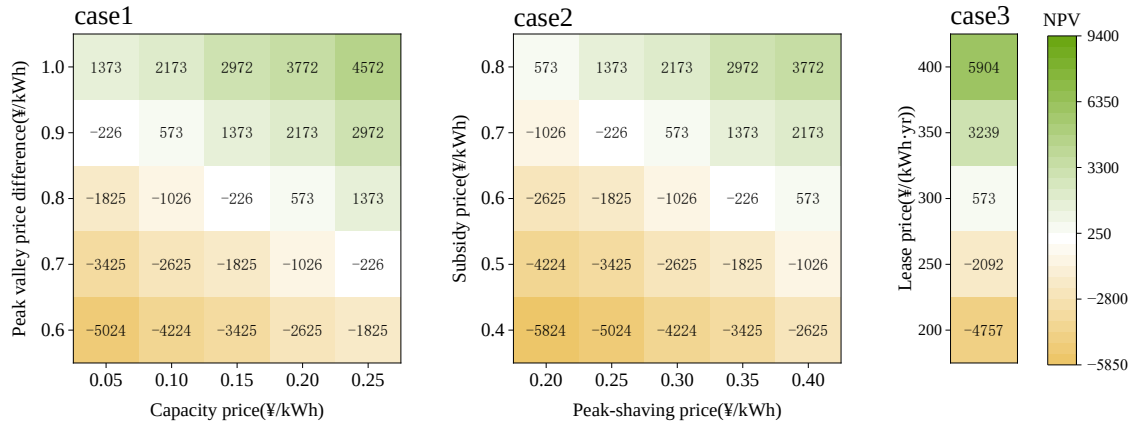


Fig. 21 Hot map of NPV in different cases / (10^4 ¥)

According to Fig. 20 and Fig. 21, in Case 4-1, when the peak-valley price difference exceeds 0.9¥/kWh

and the capacity price exceeds 0.2¥/kWh, the IRR of the project reaches 8.5% and the NPV is 2173×10^4 ¥. When the peak-valley price difference exceeds 1.0¥/kWh and the capacity price exceeds 0.2¥/kWh, the IRR of the project reaches 10.9%, and the project economy is excellent. According to the data of July, 2023, there are 16 provinces in China where the peak-valley price difference exceeds 0.9, and the standard of capacity price in Shandong Province is 0.0991¥/kWh, which is not far from the above investment conditions. However, if only rely on the peak-valley price difference to make profits, the peak-valley price difference needs to exceed 1.1¥/kWh, which is a condition that almost no province in China can stably meet the requirements at present. On the whole, the combination of "peak-valley price difference" and "capacity price" can have good economic benefits.

Comparatively speaking, the economic benefit of Case 4-2 is relatively poor. When the subsidy price exceeds 0.7¥/kWh and the peak shaving price exceeds 0.3¥/kWh, NPV is positive. When the subsidy price exceeds 0.8¥/kWh and the peak shaving price exceeds 0.3¥/kWh, the IRR of the project can reach above 8%. At present, the peak shaving price in Qinghai Province is about 0.2¥/kWh, and the subsidy price is 0.5¥/kWh. However, the income of subsidy prices is difficult to actually account for. On the whole, the combination of "peak shaving price" and "subsidy price" is difficult to obtain good economic benefits.

In Case 4-3, when the rental fee reaches 325¥/(kWh·yr), IRR reaches 8.07% and NPV is 1906×10^4 ¥. When the rental fee reaches 350¥/(kWh·yr), the IRR reaches 10.1%, and the NPV is 3239×10^4 ¥, and the economic benefit is excellent. According to the results of benefit allocation in Section 5.2.2, the daily net income of SES in Distribution mode 2 is 13.087×10^4 ¥, which can reach 799.6¥/(kWh·yr) when converted into rental fee. And the IRR is 40.4%, which has certain reference value. At present, the rental price in market is generally 160-230¥/(kWh·yr), so it is difficult to achieve high economic benefits only by renting capacity.

To sum up, the energy storage power station can consider multi-channel income mode, and obtain satisfactory return on investment through the combination of "peak-valley price difference" + "capacity price" + "peak-shaving price" + "rental fee".

6 Conclusion

In response to the increasing participation of NEPSs in the markets in the western regions of China, this paper creatively proposes a novel trading framework for a NEPSs-SES alliance in the power-green certificate market. In view of the strong conservatism of the robust model, this paper uses the scenario generation method to improve the uncertainty interval of RO, and constructs a two-stage RO method to solve the transaction model. Then, in order to comprehensively consider the contribution of members to the alliance in various factors, rather than just the income aspect, the E-S benefit distribution framework is proposed, which takes into account the factors such as risk, investment and net income. Finally, the economic analysis method is used to innovatively study the development prospect of SES. The main conclusions of this study are summarized as follows:

(1) The two-stage RO with improved uncertainty intervals proposed in this paper exhibits better economic benefits compared to traditional RO. The use of the improved uncertainty intervals in the two-stage RO better captures the volatility of NEPSs output, reducing the gap between the bid quantity and the actual output. Consequently, it leads to a 0.3% increase in the net income of the alliance.

(2) The adoption of SES demonstrates superior economic advantages compared to individual energy storages deployed by each NEPS. This is because SES can decrease the actual call frequency of the PES through the VES platform, leading to a reduction in the operating costs of SES and enhancing its ability to stabilize fluctuations. The analysis of an example shows that compared with energy storages equipped separately by each NEPS, the deviation penalty of NEPSs-SES mode is reduced by 66.4%, and the net income

is increased by 3.39%.

(3) The proposed E-S method further reflects the pivotal role of SES in smoothing fluctuations and improving economic benefits. Under the E-S method, the benefit of SES increased by 2.8×10^4 ¥. Meanwhile, compared with traditional Shapley value, the overall satisfaction under E-S method increased by 12.6%.

(4) The economic analysis of energy storage shows that the single income model is difficult to support the healthy development of independent energy storage operator. If only rely on a single income model, the IRR of energy storage is approximately 2% based on current market standards in China, making it challenging to maintain the commercial viability of energy storage operations. Energy storage power stations can explore a multi-channel income approach and achieve a favorable return on investment by combining “peak-valley price difference”, “capacity price”, “peak-shaving price” and “rental fee”.

(5) It is worth pointing out that according to the latest policy requirements of China, the future cooperation modes of NEPSs and energy storage mainly include three types: co-construction by crowdfunding (also known as cluster sharing), leasing and self-construction. In the next work, the impact of various cooperation modes of NEPSs and energy storage on their participation in multiple markets will be considered.

Acknowledge

This work was partially supported by the National Natural Science Foundation of China (Grant Nos. 71904049, 72174062, 72074074), the Beijing Social Science Foundations (21JCC088), the Project funded by China Postdoctoral Science Foundation (2019M650024) and the 2018 Key Projects of Philosophy and Social Science Research, Ministry of Education, China (18JZD032).

References

- [1] Harlan, T. (2022). Low-carbon Frontier: Renewable Energy and the New Resource Boom in Western China. *The China Quarterly*, 1-20.
- [2] Meng Li. Jinping Xi chaired the ninth meeting of the Financial and Economic Commission of the CPC Central Committee. GovCn n.d. https://www.gov.cn/xinwen/2021-03/15/content_5593154.htm (accessed January 17, 2024).
- [3] National data. GovCn n.d. <https://data.stats.gov.cn/easyquery.htm?cn=A01> (accessed January 17, 2024).
- [4] Ge W, Qi Z, Bin S, et al. Coordination of tradable carbon emission permits market and renewable electricity certificates market in China[J]. *Energy Economics*, 2021, 93.
- [5] Ke Q, Qi H, Yuefang D, et al. Distributionally robust unit commitment with an adjustable uncertainty set and dynamic demand response[J]. *Energy*, 2023, 262(PA).
- [6] Shaohua K, Yuchen W, Dongwei X. Battery energy scheduling and benefit distribution models under shared energy storage: A mini review[J]. *Frontiers in Energy Research*, 2023.
- [7] Li L, Peng K, Yang X, Liu K. Coordinated design of multi-stakeholder community energy systems and shared energy storage under uncertain supply and demand: A game theoretical approach. *Sustain Cities*

Soc 2024;100:105028. <https://doi.org/10.1016/j.scs.2023.105028>.

- [8] Li X, Chen L, Sun F, Hao Y, Du X, Mei S. Share or not share, the analysis of energy storage interaction of multiple renewable energy stations based on the evolution game. *Renew Energy* 2023;208:679–92. <https://doi.org/10.1016/j.renene.2023.03.010>.
- [9] Longxi L, Xilin C, Sen Z. Shared energy storage system for prosumers in a community: Investment decision, economic operation, and benefits allocation under a cost-effective way[J]. *Journal of Energy Storage*, 2022, 50.
- [10] ISHIZAKI, TAKAYUKI, KOIKE, MASAKAZU, YAMAGUCHI, NOBUYUKI, et al. Day-ahead energy market as adjustable robust optimization: Spatio-temporal pricing of dispatchable generators, storage batteries, and uncertain renewable resources[J]. *Energy economics*, 2020, 91(Sep.):104912.1-104912.15.
- [11] Dogan K, Joris D. Evaluation of photovoltaic storage systems on energy markets under uncertainty using stochastic dynamic programming[J]. *Energy Economics*, 2022, 106.
- [12] González-Garrido A, Gaztañaga H, Saez-de-Ibarra A, et al. Electricity and reserve market bidding strategy including sizing evaluation and a novel renewable complementarity-based centralized control for storage lifetime enhancement[J]. *Applied Energy*, 2020, 262(C).
- [13] Mingtao M, Huijun H, Xiaoling S, et al. Optimal sizing and operations of shared energy storage systems in distribution networks: A bi-level programming approach[J]. *Applied Energy*, 2022, 307.
- [14] Awnalisa W, Soongeol K. Analysis on impact of shared energy storage in residential community: Individual versus shared energy storage[J]. *Applied Energy*, 2021, 282(PA).
- [15] Tianhan Z, Weiqiang Q, Zhi Z, et al. Optimal bidding strategy and profit allocation method for shared energy storage-assisted VPP in joint energy and regulation markets[J]. *Applied Energy*, 2023, 329.
- [16] Chen C, Sun H, Shen X, et al. Two-stage robust planning-operation co-optimization of energy hub considering precise energy storage economic model[J]. *Applied Energy*, 2019, 252.
- [17] Wei F, Liwei J, Zhongfu T, et al. Two-stage distributionally robust optimization model of integrated energy system group considering energy sharing and carbon transfer[J]. *Applied Energy*, 2023, 331.
- [18] Zakaria A, Ismail FB, Lipu MSH, et al. Uncertainty models for stochastic optimization in renewable energy applications[J]. *Renew Energy* 2020. 145: 1543–71.
- [19] Simone P, Luca M, Emanuele M, et al. A novel stochastic model for flexible unit commitment of off-grid microgrids[J]. *Applied Energy*, 2023, 331.
- [20] Fei M, Jiatang Z, Jixiang L, et al. Stochastic optimal operation model for a distributed integrated energy

system based on multiple-scenario simulations[J]. *Energy*,2021,219.

- [21] Yixin L, Li G, Chengshan W. Economic Dispatch of Microgrid Based on Two Stage Robust Optimization [J]. *Proceedings of the CSEE*,2018,38(14):4013-4022+4307.
- [22] Wu M, Xu J, Zeng L, et al. Two-stage robust optimization model for park integrated energy system based on dynamic programming[J]. *Applied Energy*,2022. 308:118249.
- [23] Álvaro C G,Luis B,Raquel B G. Robust transmission network expansion planning considering non-convex operational constraints[J]. *Energy Economics*,2021(prepublish).
- [24] Hou W, Wei H, Zhu R. Data-driven multi-time scale robust scheduling framework of hydrothermal power system considering cascade hydropower station and wind penetration[J]. *IET Gener Transm Distrib* 2019. 13(6):896–904.
- [25] Shen J, Cheng C, Zhang X, Zhou B. Coordinated operations of multiple reservoir cascaded hydropower plants with cooperation benefit allocation. *Energy* 2018. 153: 509–18.
- [26] Jie Z and Wei L. Review of Revenue Allocation Method for Virtual Power Plants. 2022 IEEE International Conference on Power Systems and Electrical Technology (PSET), Aalborg, Denmark, 2022, pp. 430-433.
- [27] Andrey C,David P,Janusz B, et al. Can cross-border transmission expansion lead to fair and stable cooperation? Northeast Asia case analysis[J]. *Energy Economics*,2019,84(C).
- [28] Liwei J,Zhe Y,Qingqing Z, et al. Nearly-zero carbon optimal operation model and benefit allocation strategy for a novel virtual power plant using carbon capture, power-to-gas, and waste incineration power in rural areas[J]. *Applied Energy*,2022,310.
- [29] Liu N, Cheng M, Yu X, Zhong J, Lei J. Energy-sharing provider for PV prosumer clusters: A hybrid approach using stochastic programming and stackelberg game. *IEEE Trans Ind Electron* 2018;65:6740–50. <https://doi.org/10.1109/tie.2018.2793181>.
- [30] Leilei Z,Yixun X,Hongbin S, et al. Benefit allocation for combined heat and power dispatch considering mutual trust[J]. *Applied Energy*,2023,345.
- [31] Fang F,Yu S,Liu M. An Improved Shapley Value-Based Profit Allocation Method for CHP-VPP[J]. *Energy*,2020,213.
- [32] Min S,Yu W,Yong L. Investment and Production Strategies of Renewable Energy Power under the Quota and Green Power Certificate System[J]. *Energies*,2022,15(11).
- [33] Altan A, Karasu S, Zio E. A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer. *Appl Soft Comput*

2021;100:106996. <https://doi.org/10.1016/j.asoc.2020.106996>.

- [34] Karasu S, Altan A. Crude oil time series prediction model based on LSTM network with chaotic Henry gas solubility optimization. *Energy (Oxf)* 2022;242:122964. <https://doi.org/10.1016/j.energy.2021.122964>.
- [35] Studies from Aalto University Update Current Data on Renewable Energy (Optimization of Photovoltaic and Wind Generation Systems for Autonomous Microgrids With Pev-parking Lots)[J]. 2022(Jan.18):686.
- [36] Li K, Yang F, Wang L, et al. A scenario-based two-stage stochastic optimization approach for multi-energy microgrids[J]. *Applied Energy*, 2022, 322: 119388.
- [37] Zeng B,Zhao L. Solving two-stage robust optimization problems using a column-and-constraint generation method[J]. *Operations Research Letters*,2013,41(5).
- [38] Yaxian W,Zhenli Z,Tomas B. Benefit distribution in shared private charging pile projects based on modified Shapley value[J]. *Energy*,2023,263(PB).
- [39] Lin B,Jia Z. Is emission trading scheme an opportunity for renewable energy in China? A perspective of ETS revenue redistributions[J]. *Applied Energy*,2020,263(C).
- [40] Chenfei L,Huang H,Yue Fen. Analysis of New Energy Storage Policies and BusINEPSs models of Shandong Province [J].*Sino-Global Energy*,2022,27(11):86-92.
- [41] Yong K. New energy storage helps energy transformation[EB/OL]. 2023-03-29[2023-09-19]. <https://kpmg.com/cn/zh/home/insights/2023/03/new-energy-storage-helps-energy-transformation.html>.
- [42] Ju C, Ding T, Jia W, Mu C, Zhang H, Sun Y. Two-stage robust unit commitment with the cascade hydropower stations retrofitted with pump stations. *Appl Energy* 2023;334:120675. <https://doi.org/10.1016/j.apenergy.2023.120675>.
- [43] Khalid M, Aguilera RP, Savkin AV, Agelidis VG. On maximizing profit of wind-battery supported power station based on wind power and energy price forecasting. *Appl Energy* 2018;211:764–73. <https://doi.org/10.1016/j.apenergy.2017.11.061>.
- [44] Zhang Q, Wu X, Deng X, Huang Y, Li C, Wu J. Bidding strategy for wind power and Large-scale electric vehicles participating in Day-ahead energy and frequency regulation market. *Appl Energy* 2023;341:121063. <https://doi.org/10.1016/j.apenergy.2023.121063>.
- [45] Keyif E, Hornung M, Zhu W. Optimal configurations and operations of concentrating solar power plants under new market trends. *Appl Energy* 2020;270:115080.
- [46] Wu Y, Wu J, De G. Research on trading optimization model of virtual power plant in medium- and long-term market. *Energies* 2022;15:759. <https://doi.org/10.3390/en15030759>.

[47] Dfcfw.com n.d. https://pdf.dfcfw.com/pdf/H3_AP202302161583254743_1.pdf?1676581098000.pdf
(accessed January 30, 2024).

Appendix A

1) PES constraints

$$0 \leq P_{PES_char}^t \leq (1 - U_t^{PES}) P_{PES_char}^{\max} \quad (1)$$

$$0 \leq P_{PES_dis}^t \leq U_t^{PES} P_{PES_dis}^{\max} \quad (2)$$

$$E_{PES}^{\min} \leq E_{PES}^{t+1} \leq E_{PES}^{\max} \quad (3)$$

Where, $P_{PES_char}^{\max}$ and $P_{PES_dis}^{\max}$ are the maximum charging power and discharging power of PES, respectively. U_t^{PES} indicates the charge and discharge state of PES. 1 indicates discharge, and 0 indicates charge. $E_s^{\min}$ and $E_s^{\max}$ are the bounds of SOC for PES.

2) Shapley value method

Shapley value is a prevalent strategy of benefit allocation and widely applied in power system, which allocates revenue based on each player's marginal contribution to the alliance. The benefit obtained by the player k is as follows:

$$B_k = \sum \frac{(s-1)!(n-s)!}{n!} \cdot [B(S) - B(S-k)] \quad (4)$$

Where, N is the set of players, including NEPSs and SES. n is the number of players in N . S is a subset of N , representing a sub-coalition of some players. s is the number of players in S . $B(S)$ is the income of sub-coalition S . $B(S-k)$ is the income of alliance S excluding member k . Thus, $B(S) - B(S-k)$ denotes the marginal benefit of player k to the sub-coalition S . B_k denotes the benefit gained by player k based on Shapley value method.

In addition, the following conditions should be satisfied for players to maintain cooperation: Individual profits increase and the sum of benefit before and after distribution remains unchanged, as shown in Eq.(5).

$$\begin{cases} B_k \geq X_k \\ \sum_{k \in S} B_k = B(S) \end{cases} \quad (5)$$

Where, X_k is the income that player k receives by not participating in the alliance.

3) Entropy weight method

Entropy weight method estimates the objective weight based on the variability of indicators. The specific steps are as follows:

(1) Data standardization. Let y_{ij} be the standard value of the evaluation indicator j of the player i . To ensure that each indicator value is greater than 0, data is standardized by the following equation:

$$y_{ij} = \left[\frac{x_{ij} - x_{\min j}}{x_{\max j} - x_{\min j}} \right] \times 0.9 + 0.1 \quad (6)$$

Where, $x_{\max j}$ and $x_{\min j}$ are the initial maximum and minimum values of indicator j , respectively.

(2) Calculate the proportion P_{ij} of the evaluation indicator j of player i .

$$P_{ij} = y_{ij} / \sum_{i=1}^N y_{ij} \quad (7)$$

(3) Calculate the entropy e_j of the evaluation indicator j .

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^N P_{ij} \ln P_{ij} \quad (8)$$

(4) Calculate the weight W_j of the evaluation indicator j .

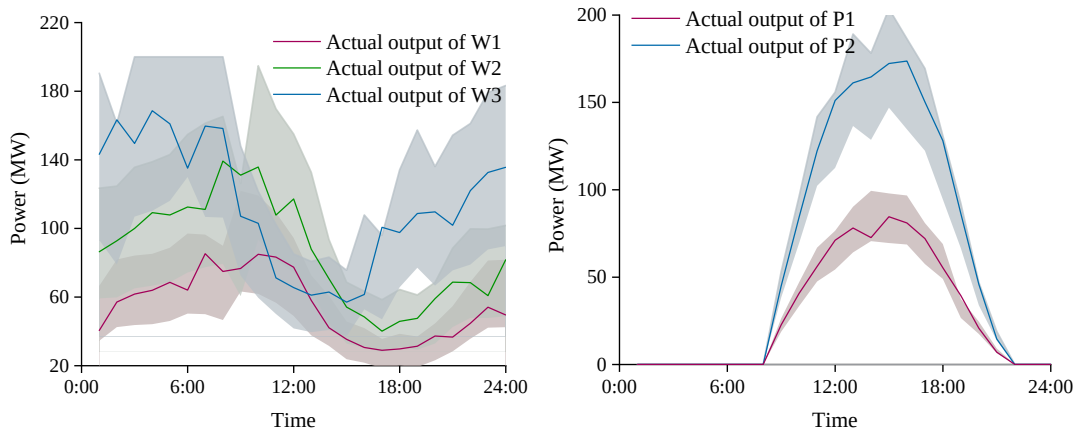
$$W_j = (1 - e_j) / \sum_{j=1}^M (1 - e_j) \quad (9)$$

(5) Calculate the comprehensive weight value σ_i of the player i .

$$\sigma_i = \sum_{j=1}^M W_j P_{ij} \quad (10)$$

Appendix B

1) Fig. B1 Forecast/Actual output of NEPSs in the traditional RO



2)The NEPSs characteristics of entropy weight method

Table B1 The NEPSs characteristics of entropy weight method

	Distribution mode 1			Distribution mode 2		
	Risk factor	Investment factor	Net income factor	Risk factor	Investment factor	Net income factor
NEPS1	94.71	13.61	44.08	94.71	13.61	42.20
NEPS2	79.12	20.41	70.15	79.12	20.41	72.47
NEPS3	0	27.21	92.51	0	27.21	90.74
NEPS4	172.06	8.13	21.26	172.06	8.13	20.69
NEPS5	156.26	16.25	46.67	156.26	16.25	47.07

4) The formula of energy storage costs and benefits.

The net benefit of energy storage is as follows:

$$R_{net,ES} = R_{ES} - C_{ES} \quad (11)$$

$$R_{ES} = U_{diff} R_{diff} + U_{ca} R_{ca} + U_{ad} R_{ad} + U_{subsidy} R_{subsidy} + U_{rent} R_{rent} \quad (12)$$

Where, $R_{net,ES}$ is the net income of ES. R_{ES} and C_{ES} are the revenue and cost of energy storage, respectively. R_{diff} , R_{ca} , R_{ad} , $R_{subsidy}$ and R_{rent} are the income from price difference, capacity compensation, peaking, subsidy and lease, respectively. The cost of energy storage includes investment cost and operating cost, and the specific expression is similar to the cost of NEPS, which can be referred to Eq. (8)-(9).