

Article

Cost Allocation Mechanism for Deep Peak Regulation in Power Systems Based on Cooperative Game Theory for Multiple Peak Regulation Demand Entities

Mengjie Liu ^{1,*}, Yi Qiang ², Mengyuan Qi ³, Zhenghui Zhao ⁴  and Zhijian Ling ⁴ ¹ State Grid Hebei Service Center, Shijiazhuang 050021, China² State Grid Hebei Electric Power Co., Ltd., Shijiazhuang 050021, China; qiangsjzyi44@163.com³ State Grid Shijiazhuang Electric Power Supply Company, Shijiazhuang 050051, China; qimengyuan92@163.com⁴ School of Electrical Information Engineering, Jiangsu University, Zhenjiang 212013, China; zhzhao@ujs.edu.cn (Z.Z.); lzj1991@ujs.edu.cn (Z.L.)

* Correspondence: 15832173312@163.com

Abstract

As the scale of renewable energy integration continues to expand, the uncertainty and variability of power system operation has increased. Meanwhile, peak regulation resources have become increasingly diverse, making the formation of peak regulation costs more complex. Existing allocation mechanisms therefore have difficulty directly linking the temporal power profile of each entity to its contribution to the optimized deep peak regulation cost and the corresponding cost responsibility. This paper applies the standard Shapley value framework to deep peak regulation cost allocation involving multiple peak regulation demand entities. An energy-preserving substitute scenario method is applied to heterogeneous demand entities. The actual profiles of coalition members are retained, whereas the profiles of nonmembers are replaced by their mean values, thereby removing temporal fluctuations while preserving total energy over the dispatch horizon. For each coalition-specific net load scenario, a dispatch optimization model considering the piecewise deep regulation capability of thermal units and the intertemporal constraints of pumped storage are re-solved, and the resulting minimum cost is used to construct the coalition cost function. The signed Shapley value is then used to calculate the average marginal cost effect of each entity across all coalitions, after which a practical positive contribution settlement rule converts the signed values into nonnegative and budget-balanced charges. A provincial system case study shows that, compared with energy proportional and peak power proportional allocation, the proposed method explicitly accounts for the temporal characteristics and interactions of heterogeneous power profiles and links them to changes in the optimized deep peak regulation cost through coalition-specific re-optimization.

Keywords: cooperative game; Shapley value; deep peak regulation; cost allocation

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1. Introduction

In recent years, driven by the global energy transition and emission reduction targets, renewable energy has developed rapidly, with its installed capacity increasing substantially [1]. However, the variability, intermittency, and counter peak characteristics of renewable generation increase net load variability and complicate real-time power balancing [2,3]. As the flexibility available from conventional thermal units becomes increasingly

constrained, the demand for deep peak regulation services continues to grow [4]. Meanwhile, commonly used peak regulation cost allocation methods are mainly based on energy consumption, peak demand, or electricity bill shares and therefore do not directly reflect how the timing and direction of heterogeneous power profiles affect net load variation and optimized regulation costs [5]. Consequently, the entities that cause additional peak regulation costs may not bear the corresponding expenses. A practical settlement rule is therefore needed to translate the marginal effects of heterogeneous temporal profiles on optimized system costs into recoverable charges.

Existing studies on deep peak regulation optimization have mainly focused on the coordinated operation of thermal power, energy storage, pumped storage, nuclear power, and demand–response resources. Reference [6] studied the deep peak regulation cost of thermal power units and showed that deep peak regulation can facilitate renewable energy integration, although it increases unit operating costs. References [7,8] developed coordinated thermal power–energy storage models incorporating wind curtailment penalties and storage revenues to optimize thermal unit output and storage charging and discharging. Reference [9] incorporated the short-term start–stop capability of thermal units into peak regulation strategies, reducing daily operating costs and improving system-level regulation feasibility. Reference [10] examined the coordinated operation of pumped storage and coal-fired units in reducing deep peak regulation costs and wind curtailment. References [11,12] integrated nuclear power into the peak regulation framework, established cost models to quantify the cost of nuclear power participation, and demonstrated its feasibility in providing ancillary services. These studies improve system flexibility and quantify the economic effects of thermal deep regulation, energy storage, pumped storage, nuclear power, and renewable curtailment. Some studies also include resource-specific operating costs, storage revenues, curtailment penalties, or compensation terms in the dispatch objective. However, these economic terms are primarily used to optimize system operation or evaluate flexibility providers, they are not further decomposed to identify the marginal cost effects of the heterogeneous load and renewable energy profiles that induce peak regulation demand.

In terms of cost allocation, electricity markets generally follow the cost causation principle, under which entities that increase system costs should bear the corresponding expenses [13]. Existing studies have explored cost allocation from the perspectives of ancillary service markets, electricity pricing mechanisms, risk contribution, and shared energy storage [14–17], providing a theoretical basis for related allocation mechanisms. To address the more complex allocation problem associated with deep peak regulation, cooperative game theory and contribution evaluation methods have also been introduced. Cooperative game-based studies have mainly focused on economic allocation among supply-side peak regulation resources. Reference [18] allocated wind integration-related peak regulation costs among thermal power units. Reference [19] proposed a modified Shapley value-based profit allocation method for wind–thermal cooperation, aiming to strengthen the incentives for thermal units to participate in deep peak regulation. Reference [20] considered compensation allocation in coordinated thermal power–energy storage deep peak regulation. Although these studies improved the allocation of costs or profits among flexibility providers, they mainly addressed economic coordination on the supply side rather than identifying the entities that induce peak regulation demand. As a result, costs associated with net load variations may be assigned to thermal units, energy storage, or other service providers rather than to the entities responsible for those variations. Because peak regulation demand is driven by net load variation, load fluctuations, like renewable energy fluctuations, directly affect both the magnitude and timing of regulation requirements. Therefore, excluding load-side entities may result in incomplete

cost attribution. Reference [21] incorporated load-side responsibility into the deep peak regulation cost allocation framework, but its internal allocation among load entities mainly relied on waveform similarity indicators. Such indicators measure the similarity between curve shapes but do not directly quantify the change in optimized operating costs caused by each entity. Consequently, they cannot fully capture the nonlinear cost effects arising from the piecewise deep peak regulation constraints of thermal units, the intertemporal operation of pumped storage, and the temporal complementarity among different entities. Reference [22] further considered peak regulation demand entities and thermal units, but its responsibility evaluation still depended on correction indicators, making the results dependent on the selected indicators rather than being directly linked to changes in optimized system costs.

Overall, the existing literature presents two main limitations. First, deep peak regulation optimization studies mainly quantify and reduce aggregate system costs without further attributing the incremental cost to the heterogeneous profiles that induce regulation demand. Second, existing allocation approaches either focus on economic coordination among supply-side flexibility providers or rely on scale-based, similarity-based, or correction indicator-based rules. These approaches do not directly construct participant responsibility from coalition-specific changes in optimized system costs. To address these gaps, this paper applies the standard Shapley value framework to the deep peak regulation cost allocation problem involving multiple demand entities. The main contribution lies in the modeling of heterogeneous participants and the construction of coalition-specific cost functions. The main contributions are as follows:

(1) A participant structure that distinguishes peak regulation demand entities from supply-side flexibility resources is established. Residential load, industrial load, commercial load, wind power, and PV power are modeled as independent peak regulation demand entities, whereas thermal units and pumped storage are treated as supply-side flexibility resources. This structure enables heterogeneous load and renewable energy profiles to be evaluated within the same marginal cost assessment framework.

(2) An energy-preserving substitute scenario method is applied to heterogeneous entity profiles to quantify their cost effects. For each coalition, the actual profiles of the included entities are retained, whereas the actual profile of each excluded entity is replaced by a constant profile equal to its mean value, thereby removing its temporal fluctuations while preserving its total energy. The deep peak regulation dispatch problem is then re-optimized for each coalition-specific net load scenario, and the resulting minimum cost is used to define the coalition cost. This procedure links the temporal characteristics of each entity to changes in the optimized system cost while accounting for thermal unit piecewise regulation, pumped storage intertemporal constraints, and interactions among entity profiles.

(3) The signed standard Shapley value is applied to measure each entity's order independent average marginal cost effect across all coalitions. For practical cost recovery, only positive contributions are used to determine nonnegative charges, thereby ensuring full recovery of the remunerated deep peak regulation cost.

2. Deep Peak Regulation Modeling and Cost Calculation

For a given net load profile, the deep peak regulation dispatch model minimizes the total system cost associated with remunerated thermal regulation, pumped storage operation, unit startup and shutdown, and renewable energy curtailment, subject to thermal unit commitment, reserve, ramping, pumped storage, and renewable output constraints. The operating status, startup, shutdown, and pumped storage mode variables are binary, whereas the remaining dispatch variables are continuous. Because the objective function

and all constraints are linear, the resulting problem is formulated as a mixed-integer linear programming model.

The energy-preserving substitute scenario method is then used to construct the net load profile associated with each coalition. The dispatch model is independently re-solved for every coalition, and the resulting minimum costs are used to construct the coalition characteristic function and calculate the signed Shapley values. Figure 1 summarizes the overall procedure.

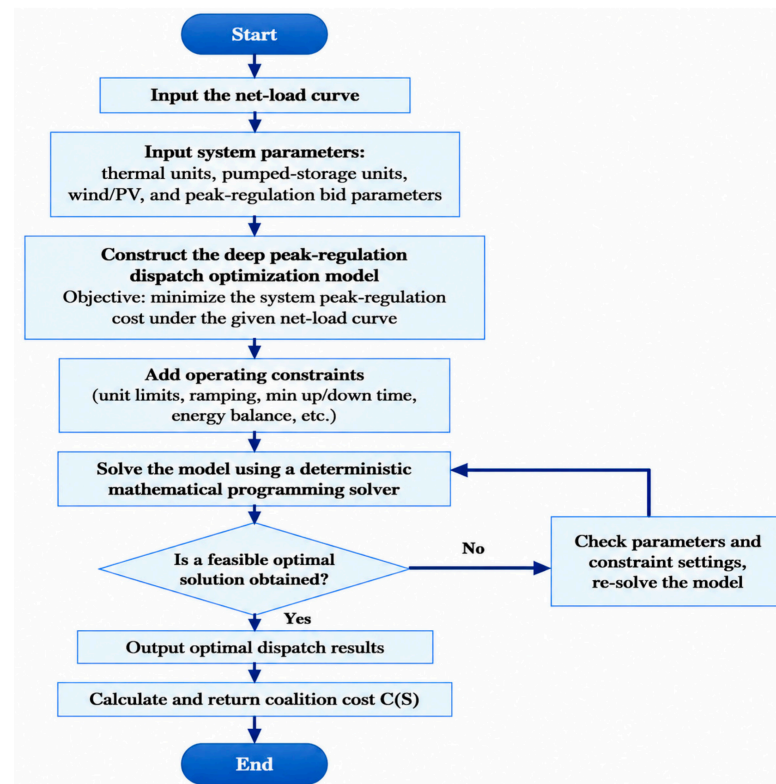


Figure 1. Calculation procedure for coalition-specific deep peak regulation costs.

2.1. Deep Peak Regulation Cost Function

The objective of the deep peak regulation optimization model is to minimize the total deep peak regulation cost under a given net load profile. The total cost comprises three components: the remunerated peak regulation cost of thermal power units C_g , the pumping operation cost of pumped storage stations C_{pu} , and the curtailment cost of wind power and PV power C_{cur} , as shown in Equation (1):

$$\begin{cases} c(\mathbf{L}) = \min(C_g + C_{pu} + C_{cur}) \\ C_g = \sum_{i \in G_C} \sum_{t \in T} \left(\sum_{o \in \Omega_D} \lambda_{i,o}^D P_{i,t,o}^D + y_{i,t} C_{i,t}^{SU} + z_{i,t} C_{i,t}^{SD} \right) \\ C_{pu} = \sum_{t \in T} \sum_{g \in G_{pu}} c_g^{pu} P_{g,t}^{pu,S} \\ C_{cur} = \sum_{t \in T} \sum_{v \in G_V} V_{LE} P_{v,t}^{cur} \end{cases} \quad (1)$$

where $c(\mathbf{L})$ denotes the minimum total deep peak regulation cost under net load profile $\mathbf{L}$; G_C is the set of thermal power units; Ω_D is the set of deep peak regulation segments; G_{pu} is the set of pumped storage units; G_V is the set of renewable energy sources; T is the set of dispatch periods; $\lambda_{i,o}^D$ is the bid price of thermal power unit i in the o -th deep peak regulation segment; $P_{i,t,o}^D$ is the cleared peak regulation capacity of unit i in the o -th deep peak regulation segment during period t ; $y_{i,t}$ and $z_{i,t}$ are the startup and shutdown

variables of thermal unit i , taking a value of 1 when the corresponding action occurs and 0 otherwise; $C_{i,t}^{SU}$ and $C_{i,t}^{SD}$ are the corresponding startup and shutdown costs; c_g^{Pu} is the pumping electricity bid price of pumped storage unit g ; $P_{g,t}^{Pu,S}$ is the pumping power of pumped storage unit g during period t ; V_{LE} is the unit energy curtailment cost; and $P_{v,t}^{cur}$ is the curtailed power of renewable energy source v during period t .

A fixed startup cost is adopted for each thermal unit class. The dependence of startup cost on the preceding offline duration, such as hot and cold start conditions, is not explicitly modeled in this study. This assumption reduces the number of additional binary variables while retaining the principal unit commitment characteristics relevant to the peak regulation cost calculation.

2.2. Constraints

In addition to the objective function, the dispatch model is subject to the following operating constraints:

(1) System balance constraint

$$\sum_{i \in G_C} P_{i,t} + \sum_{v \in G_V} P_{v,t} + \sum_{g \in G_{Pu}} (P_{g,t}^{Pu,G} - P_{g,t}^{Pu,S}) = \sum_{j \in J} D_{j,t} \quad t \in T \quad (2)$$

where $P_{i,t}$ is the output of thermal power unit i during period t ; $P_{v,t}$ is the actual grid-connected output of renewable energy source v during period t ; $P_{g,t}^{Pu,G}$ and $P_{g,t}^{Pu,S}$ are the generation power and pumping power of pumped storage unit g during period t , respectively; $D_{j,t}$ is the demand of load entity j ; and J denotes the set of load entities.

(2) System reserve constraint

$$\begin{cases} \sum_{i \in G_C} (u_{i,t} P_i^{max} - P_{i,t}) \geq R_t^{Ureq} & t \in T \\ \sum_{i \in G_C} (P_{i,t} - u_{i,t} P_i^{min}) \geq R_t^{Dreq} & t \in T \end{cases} \quad (3)$$

where $u_{i,t}$ is the binary operating status variable of thermal unit i , taking a value of 1 when the unit is online and 0 otherwise; R_t^{Ureq} and R_t^{Dreq} are the upward and downward reserve requirements of the system during period t , respectively; P_i^{max} and P_i^{min} are the maximum and minimum technical output limits of unit i , respectively.

(3) Unit output constraint

$$\begin{cases} u_{i,t} P_i^{min} \leq P_{i,t} \leq u_{i,t} P_i^{max} & i \in G_C, t \in T \\ P_{i,t} + \sum_{o \in \Omega_D} P_{i,t,o}^D \geq u_{i,t} P_{i,t}^{b,min} & i \in G_C, t \in T \\ P_{i,t,o}^D \leq u_{i,t} P_{i,o}^{max} & i \in G_C, t \in T, o \in \Omega_D \\ u_{g,t}^{Pu,G} P_g^{G,min} \leq P_{g,t}^{Pu,G} \leq u_{g,t}^{Pu,G} P_g^{G,max} & g \in G_{Pu}, t \in T \\ u_{g,t}^{Pu,S} P_g^{S,min} \leq P_{g,t}^{Pu,S} \leq u_{g,t}^{Pu,S} P_g^{S,max} & g \in G_{Pu}, t \in T \\ P_{v,t} + P_{v,t}^{cur} = \widetilde{P}_{v,t} & v \in G_V, t \in T \\ 0 \leq P_{v,t}^{cur} \leq \widetilde{P}_{v,t} & v \in G_V, t \in T \end{cases} \quad (4)$$

where $P_{i,t}^{b,min}$ is the minimum technical output of unit i under basic peak regulation during period t ; $P_{i,o}^{max}$ is the maximum capacity of deep peak regulation segment o ; $P_g^{G,min}$ and $P_g^{G,max}$ are the minimum and maximum generation power of pumped storage unit g , respectively; $P_g^{S,min}$ and $P_g^{S,max}$ are the minimum and maximum pumping power of pumped storage unit g , respectively; $u_{g,t}^{Pu,G}$ and $u_{g,t}^{Pu,S}$ are the binary generating and pumping status variables, taking a value of 1 when the corresponding mode is active and 0 otherwise; and $\widetilde{P}_{v,t}$ is the forecast output of renewable energy source v during period t .

Each deep peak regulation segment is represented by a continuous decision variable $P_{i,t,o}^D$, bounded by the available capacity $P_{i,o}^{D,max}$ of that segment. The corresponding cost term $\lambda_{i,o}^D P_{i,t,o}^D$ enters the objective function linearly. Because the segment bid prices are non-decreasing, lower priced segments are selected before higher priced segments. Therefore, the piecewise linear regulation cost is directly incorporated into the MILP model.

(4) Ramp rate constraints

$$\begin{cases} P_{i,t} - P_{i,t-1} \leq \Delta P_i^U + (1 - u_{i,t-1})P_i^{max} & i \in G_C, t \in T \\ P_{i,t-1} - P_{i,t} \leq \Delta P_i^D + (1 - u_{i,t})P_i^{max} & i \in G_C, t \in T \end{cases} \quad (5)$$

where ΔP_i^U and ΔP_i^D represent the upward and downward ramping limits of unit i , respectively.

(5) Minimum up- and down-time constraints

The startup and shutdown variables are linked to changes in the operating status of each thermal unit, and the minimum up- and down-time requirements are expressed as:

$$\begin{cases} y_{i,t} - z_{i,t} = u_{i,t} - u_{i,t-1} & i \in G_C, t \in T \\ y_{i,t} + z_{i,t} \leq 1 & i \in G_C, t \in T \\ \sum_{\tau=t}^{t+T_i^{on}-1} u_{i,\tau} \geq T_i^{on} y_{i,t} & i \in G_C, t \in T \\ \sum_{\tau=t}^{t+T_i^{off}-1} (1 - u_{i,\tau}) \geq T_i^{off} z_{i,t} & i \in G_C, t \in T \end{cases} \quad (6)$$

where T_i^{on} and T_i^{off} represent the minimum on-time and off-time requirements of unit i , respectively.

(6) Pumped storage constraints

During each dispatch period, a pumped storage station can operate in either generating or pumping mode, but not simultaneously. The operating state of each unit must be consistent with the station-level operating mode. The upper reservoir energy level follows an intertemporal balance equation and is bounded by its allowable range. A terminal energy balance constraint is also imposed to avoid end-of-horizon effects [23,24].

$$\begin{cases} u_t^{Pu,G} + u_t^{Pu,S} \leq 1 & t \in T \\ u_{g,t}^{Pu,G} \leq u_t^{Pu,G} & g \in G_{Pu}, t \in T \\ u_{g,t}^{Pu,S} \leq u_t^{Pu,S} & g \in G_{Pu}, t \in T \\ Q_t^U = Q_{t-1}^U + \sum_{g \in G_{Pu}} \eta_S P_{g,t}^{Pu,S} \Delta t - \sum_{g \in G_{Pu}} \frac{P_{g,t}^{Pu,G} \Delta t}{\eta_G} & t \in T \\ Q_{min}^U \leq Q_t^U \leq Q_{max}^U & t \in T \\ Q_0^U = Q_{|T|}^U \end{cases} \quad (7)$$

where $u_t^{Pu,G}$ and $u_t^{Pu,S}$ denote the station-level generating and pumping status variables, respectively, and $u_{g,t}^{Pu,G}$ and $u_{g,t}^{Pu,S}$ are the corresponding unit-level status variables. $P_{g,t}^{Pu,G}$ and $P_{g,t}^{Pu,S}$ denote the generating and pumping powers of unit g , while η_G and η_S are the generating and pumping efficiencies. Q_t^U denotes the continuous energy equivalent storage level of the upper reservoir, measured in MWh. Pumping increases the stored energy by $\eta_S P_{g,t}^{Pu,S} \Delta t$, whereas generation decreases it by $P_{g,t}^{Pu,G} \Delta t / \eta_G$. Under a constant effective head

H , the physical water volume V_t^U is converted to the corresponding energy equivalent storage level as follows:

$$Q_t^U = \frac{\rho g_0 H V_t^U}{3.6 \times 10^9} \quad (8)$$

where ρ is the water density, g_0 is the gravitational acceleration, H is the assumed constant effective head, and V_t^U is the physical water volume in the upper reservoir.

2.3. Construction of Substitute Scenarios for Multiple Peak Regulation Demand Entities

The dispatch model above determines the minimum cost for a given net load profile. For multi-entity cost allocation, comparable substitute scenarios [25] are constructed to evaluate how retaining or replacing each entity's temporal profile affects net load fluctuations and the optimized deep peak regulation cost. To this end, each entity's profile is decomposed into a mean component and a zero-sum temporal deviation. For each coalition, the actual profiles of its members are retained, while those of nonmembers are replaced by their mean values, preserving total energy while removing temporal fluctuations. The dispatch model is then re-optimized, and the resulting cost changes are used to evaluate each entity's marginal cost effect.

Let J denote the set of load entities. The deviation $d_{j,t}$ of the load of entity j ($j \in J$) from its mean can be expressed as:

$$d_{j,t} = D_{j,t} - \frac{1}{|T|} \sum_{\tau \in T} D_{j,\tau} \quad j \in J, t \in T \quad (9)$$

where $\frac{1}{|T|} \sum_t D_{j,t}$ denotes the mean load of entity j over the dispatch horizon T .

Let G_V denote the set of variable renewable energy sources. Because renewable output enters the net load expression with a negative sign, the deviation contribution of renewable energy source v is defined as:

$$d_{v,t} = -P_{v,t} + \frac{1}{|T|} \sum_{\tau \in T} P_{v,\tau} \quad v \in G_V, t \in T \quad (10)$$

where $P_{v,t}$ represents the output of renewable energy source v during period t , and $\frac{1}{|T|} \sum_t P_{v,t}$ denotes its mean output over the dispatch horizon.

The system net load L_t can be expressed as:

$$L_t = \sum_{j \in J} D_{j,t} - \sum_{v \in G_V} P_{v,t} \quad t \in T \quad (11)$$

Let $N = J \cup G_V$ denote the set of peak regulation demand entities. Because each substitute profile preserves the total energy of the corresponding entity, its deviation over the dispatch horizon satisfies:

$$\sum_{t \in T} d_{n,t} = 0 \quad n \in N \quad (12)$$

Equation (12) ensures that replacing an actual profile with its mean changes only its temporal variation rather than its total energy. When all entities are replaced by their mean profiles, the resulting reference net load vector is constant and can be expressed as:

$$\bar{\mathbf{L}} = \mathbf{L} - \sum_{n \in N} \mathbf{d}_n \quad (13)$$

where $\mathbf{L}$ and $\bar{\mathbf{L}}$ denote the actual and reference net load vectors, respectively, and $\mathbf{d}_n$ denotes the deviation vector of peak regulation demand entity n from its mean profile.

The coalition scenarios are analytical counterfactual scenarios rather than physical systems in which nonmember entities are removed. All entities remain present, and only the temporal deviations of nonmembers are replaced. The resulting coalition costs are therefore comparable measures of the optimized cost effects associated with different combinations of retained deviations.

3. Peak Regulation Cost Allocation Mechanism

3.1. Determination of the Coalition Cost Function

Based on the optimized deep peak regulation costs obtained for different participant combinations in Section 2, the marginal cost assessment is formulated as a cooperative game. Each coalition corresponds to a substitute net load profile, and the minimum cost obtained by re-solving the deep peak regulation dispatch model under that profile is defined as its coalition cost. The coalition cost function is expressed as:

$$C(S) = c(\bar{\mathbf{L}} + \sum_{n \in S} \mathbf{d}_n), \quad S \subseteq N \quad (14)$$

where N denotes the set of all peak regulation demand entities; $C(S)$ is the minimum deep peak regulation cost associated with coalition S ; $c(\cdot)$ is the optimal cost function defined by the deep peak regulation dispatch model. Equation (14) maps the profiles retained in each coalition to the corresponding optimized system cost and thereby defines the characteristic function of the cooperative game.

3.2. Signed Shapley Marginal Cost Assessment and Positive Contribution Settlement

The Shapley value originates from cooperative game theory [26]. It evaluates each participant according to the weighted average of its marginal cost contributions across all possible coalitions, thereby providing an order-independent measure of its average marginal cost effect.

Let $S \subseteq N$ denote a coalition containing participant n . The marginal deep peak regulation cost contribution of participant n to coalition S is given by:

$$m_n(S) = C(S) - C(S \setminus \{n\}) = c(\bar{\mathbf{L}} + \sum_{n' \in S} \mathbf{d}_{n'}) - c(\bar{\mathbf{L}} + \sum_{n' \in S \setminus \{n\}} \mathbf{d}_{n'}) \quad (15)$$

where n' denotes a peak regulation demand participant; $S \setminus \{n\}$ represents the sub-coalition of coalition S excluding participant n ; and $\bar{\mathbf{L}}$ denotes the reference net load vector.

The standard Shapley value of participant n is then calculated as:

$$\Phi_n(C) = \sum_{\substack{S \subseteq N \\ n \in S}} \frac{(|S| - 1)!(|N| - |S|)!}{|N|!} m_n(S) \quad (16)$$

The Shapley value therefore represents the weighted average of the participant's marginal cost contributions across all possible coalitions.

By summing the Shapley values of all entities, the difference between the grand coalition cost and the reference scenario cost is obtained:

$$\sum_{n \in N} \Phi_n(C) = C(N) - C(\emptyset) = c(\mathbf{L}) - c(\bar{\mathbf{L}}) \quad (17)$$

When all peak regulation demand entities are replaced by their mean profiles, the resulting reference net load is constant. In this study, the reference profile can be ac-

commodated without activating remunerated deep peak regulation resources; hence, $C(\emptyset) = c(\bar{\mathbf{L}}) = 0$. Therefore:

$$\sum_{n \in N} \Phi_n(C) = c(\mathbf{L}) \quad (18)$$

Equation (18) confirms that the signed standard Shapley values fully allocate the deep peak regulation cost of the actual scenario. A positive value indicates that the participant increases the cost on average, whereas a negative value indicates an average cost-mitigating effect under the defined coalition cost model.

Since this study focuses on the recovery of remunerated deep peak regulation costs, participants with negative signed Shapley values are assigned zero charges, whereas the total remunerated cost is allocated among participants with positive values in proportion to their positive Shapley values. The final charge assigned to participant n is

$$C_n^{Sh} = \frac{[\Phi_n(C)]_+}{\sum_{n \in N} [\Phi_n(C)]_+} C^{PP} \quad (19)$$

$$C^{PP} = \sum_{i \in G_C} \sum_{t \in T} \left(\sum_{o \in \Omega_D} \lambda_{i,o}^D P_{i,t,o}^D + y_{i,t} C_{i,t}^{SU} + z_{i,t} C_{i,t}^{SD} \right) + \sum_{t \in T} \sum_{g \in G_{Pu}} c_g^{Pu} P_{g,t}^{Pu,S} \quad (20)$$

where $[\Phi_n(C)]_+ = \max\{\Phi_n(C), 0\}$ denotes the positive part of the Shapley value. It is equal to $\Phi_n(C)$ when $\Phi_n(C) > 0$ and is set to zero otherwise. C^{PP} denotes the total remunerated peak regulation cost to be recovered, and C_n^{Sh} denotes the final charge assigned to participant n . This rule preserves budget balance, nonnegativity, order independence, symmetry, and the null player property. However, because truncation and renormalization are nonlinear, additivity, the general dummy player property, and the exact signed marginal contribution interpretation are not retained when negative Shapley values exist. Equation (19) therefore defines a practical settlement rule rather than a standard Shapley allocation.

4. Case Study

4.1. Deep Peak Regulation Cost Analysis

A provincial power system in China is used to examine the proposed practical marginal cost-based settlement mechanism. The 24 h scheduling horizon is divided into 1 h intervals. The system has a total installed capacity of 38,400 MW, including 56 thermal units, four 300 MW pumped storage units, 6000 MW of wind power, 3000 MW of PV power, and 8000 MW of fixed output generation. The thermal fleet consists of eighteen 600 MW units, eighteen 300 MW units, and twenty 200 MW units. Table 1 summarizes the generation composition.

Table 1. Generation composition of the test system.

Power Source	Number of Units	Installed Capacity (MW)
600 MW thermal power units	18	10,800
300 MW thermal power units	18	5400
200 MW thermal power units	20	4000
Pumped storage units	4	1200
Wind power	-	6000
PV power	-	3000
Fixed output generation	-	8000
Total	-	38,400

The main operating parameters of the thermal units and the pumped storage station are listed in Tables 2 and 3, respectively. All thermal units within the same capacity class adopt the class-level operating parameters listed in Table 2.

Table 2. Class-level operating parameters of the thermal units.

Unit Capacity	P _{max} (MW)	P _{min} (MW)	Up/Down Ramp (MW/h)	Minimum Up-Time (h)	Minimum Down-Time (h)	Start-Up Cost (CNY)	Shut-Down Cost (CNY)
600 MW	600	180	180	8	6	300,000	60,000
300 MW	300	90	90	6	4	150,000	30,000
200 MW	200	100	60	4	3	100,000	20,000

Table 3. Operating parameters of the pumped storage station.

Parameter	Value
Single unit ramping limit (MW/h)	300
Pumping efficiency	0.866
Generating efficiency	0.866
Pumping bid price (CNY/MWh)	100
Equivalent energy range (MWh)	500–14,000
Initial and terminal equivalent energy (MWh)	5000

The basic peak regulation reference output of thermal units is set to 50% of their rated capacity. The upward and downward reserve requirements are both set to 5% of the hourly system load. During load valley periods, when the basic downward regulation capability is insufficient after satisfying the reserve requirements, pumped storage units and selected large-capacity thermal units are dispatched to provide additional deep peak regulation. The operating parameters of the pumped storage station are listed in Table 3.

The penalty prices for wind and PV curtailment are both set to 1500 CNY/MWh. For thermal units, each additional 5 percentage point reduction in the loading ratio below the 50% basic regulation reference defines a separate deep regulation pricing segment. The corresponding aggregate deep regulation capacities and bid prices for different thermal unit classes are listed in Table 4.

Table 4. Deep peak regulation capacities and bid prices for thermal unit classes.

Unit Capacity	Segment 1		Segment 2		Segment 3		Segment 4	
	Price (CNY/MWh)	Capacity (MW)	Price (CNY/MWh)	Capacity (MW)	Price (CNY/MWh)	Capacity (MW)	Price (CNY/MWh)	Capacity (MW)
600 MW	550	423	731	423	780	393	883	163
300 MW	600	276	782	276	833	276	936	106

Figure 2 presents the wind power, PV power, and load profiles in MW. As shown in Figure 2a, PV output peaks around midday, whereas wind output is more variable. Figure 2b shows that residential load peaks between 19:00 and 21:00, industrial load remains relatively stable, and commercial load increases during 08:00–18:00. These profiles jointly determine the net load profile shown in Figure 3.

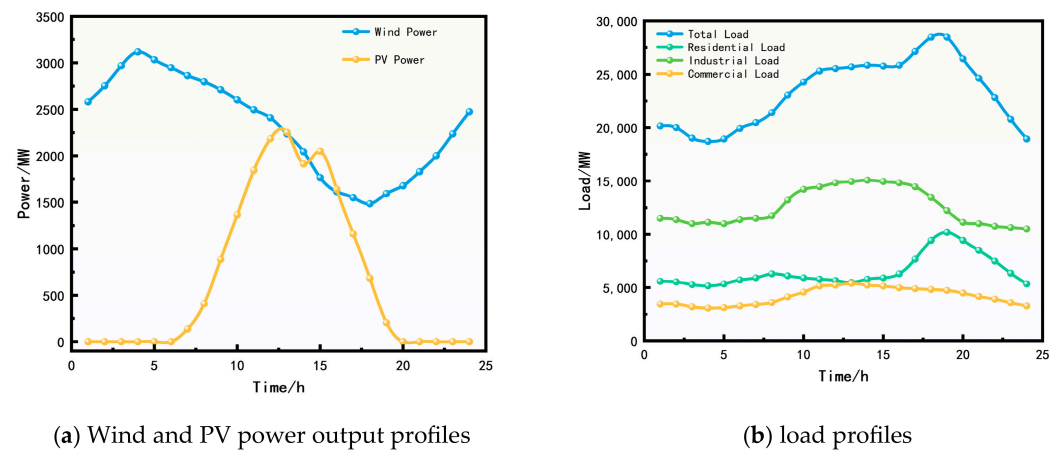


Figure 2. System load, wind power and PV power output.

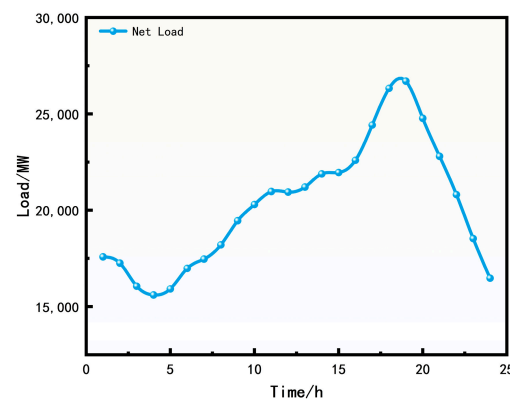


Figure 3. Actual net load curve of the regional power grid.

Based on the above data and the dispatch optimization model, the total deep peak regulation cost in the actual scenario is 147.17×10^4 CNY. No wind or PV curtailment occurs in the base case; therefore, the curtailment cost is zero. The total cost consequently consists of the remunerated deep peak regulation cost of thermal units and the pumping operation cost of pumped storage. Figure 4 shows that the 300 MW and 600 MW thermal units provide deep peak regulation during different periods by reducing their output. Figure 5 confirms that power balance is maintained throughout the 24 h dispatch horizon through the coordination of thermal generation, pumped storage operation, and renewable energy output.

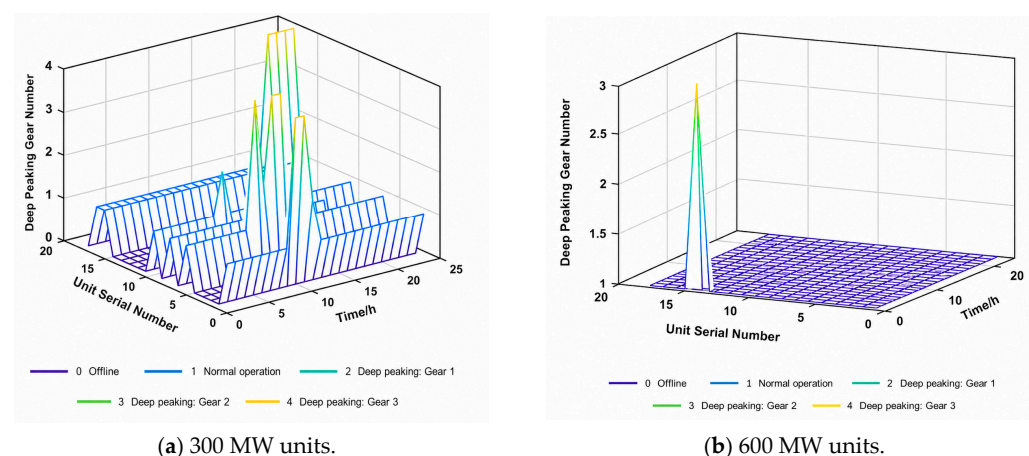


Figure 4. Deep peak regulation operation of thermal units.

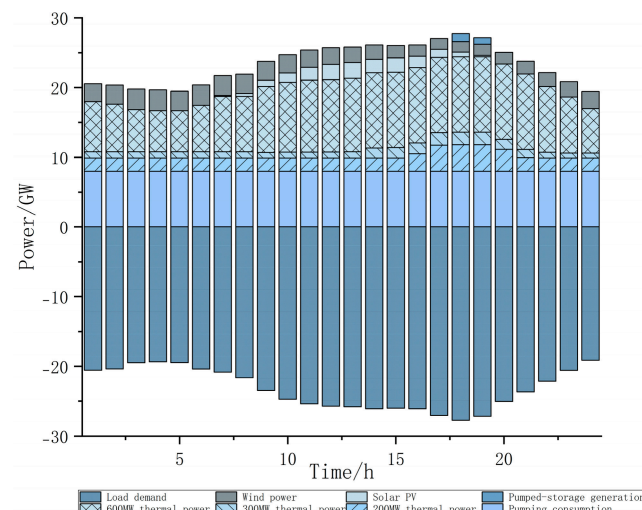


Figure 5. System power balance over the 24 h dispatch horizon.

There are five peak regulation demand entities in the system. Wind power, PV power, residential load, industrial load, and commercial load are denoted by v_1 , v_2 , l_1 , l_2 and l_3 , respectively. The set of all peak regulation demand entities can be represented as $N = \{v_1, v_2, l_1, l_2, l_3\}$. This set generates 32 coalitions, including the empty coalition. Exact enumeration is computationally feasible for the five aggregated entities considered in this case study. For systems with many individual participants, entities may first be aggregated by category or region, or the Shapley values may be approximated using random permutation or Monte Carlo sampling. Because the coalition-specific optimization problems are independent, they can also be solved in parallel. The minimum remunerated deep peak regulation cost under each coalition-specific substitute scenario is reported in Table 5.

Table 5. Remunerated deep peak regulation costs of all coalitions.

Coalition S	Cost (10^4 CNY)	Coalition S	Cost (10^4 CNY)
$\{v_1\}$	0	$\{v_1, v_2, l_2\}$	93.60
$\{v_2\}$	64.29	$\{v_1, v_2, l_3\}$	0
$\{l_1\}$	0	$\{v_1, l_1, l_2\}$	0
$\{l_2\}$	0	$\{v_1, l_1, l_3\}$	225.42
$\{l_3\}$	0	$\{v_1, l_2, l_3\}$	161.20
$\{v_1, v_2\}$	236.73	$\{v_2, l_1, l_2\}$	0
$\{v_1, l_1\}$	0	$\{v_2, l_1, l_3\}$	0
$\{v_1, l_2\}$	0	$\{v_2, l_2, l_3\}$	0
$\{v_1, l_3\}$	0	$\{l_1, l_2, l_3\}$	488.51
$\{v_2, l_1\}$	141.54	$\{v_1, v_2, l_1, l_2\}$	169.88
$\{v_2, l_2\}$	0	$\{v_1, v_2, l_1, l_3\}$	0
$\{v_2, l_3\}$	0	$\{v_1, v_2, l_2, l_3\}$	0
$\{l_1, l_2\}$	0	$\{v_1, l_1, l_2, l_3\}$	437.55
$\{l_1, l_3\}$	253.07	$\{v_2, l_1, l_2, l_3\}$	180.37
$\{l_2, l_3\}$	201.20	$\emptyset$	0
$\{v_1, v_2, l_1\}$	355.84	$\{v_1, v_2, l_1, l_2, l_3\}$	147.17

As shown in Table 5, the remunerated deep peak regulation cost varies considerably among coalitions. Several single entity and two entity coalitions, including $\{v_1\}$, $\{l_1\}$, $\{l_2\}$, $\{l_3\}$, and $\{v_1, l_1\}$, have zero remunerated cost. A zero value does not indicate the absence of profile fluctuations or balancing requirements; rather, it means that these requirements can be accommodated without activating additional remunerated deep regulation resources.

In this case study, the aggregate minimum generation level under basic peak regulation operation is 18,100 MW. Considering the available basic downward regulation capability of 1200 MW, additional remunerated deep regulation is activated when the net load falls below 16,900 MW.

Figure 6 compares the zero-cost coalition $\{v_1, l_1\}$ with the high-cost coalition $\{l_1, l_2, l_3\}$. The minimum net load of $\{v_1, l_1\}$ is 17,368.70 MW and remains above the activation threshold throughout the scheduling horizon; therefore, its remunerated cost is zero. In contrast, the net load of $\{l_1, l_2, l_3\}$ falls below the threshold during hours 0–5 and reaches a minimum of 15,607.36 MW, thereby activating additional remunerated deep regulation and producing a coalition cost of 488.51×10^4 CNY. Thus, a zero coalition cost means that no additional remunerated deep regulation is required, rather than that no regulation is required.

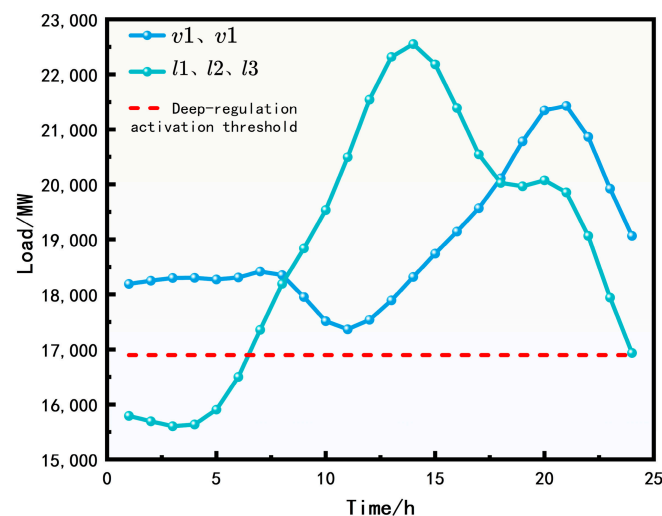


Figure 6. Coalition-specific net load profiles of a zero-cost coalition and a high-cost coalition.

It should be noted that the coalitions are analytical substitute scenarios rather than physical configurations in which entities outside a coalition are removed from the system. For each coalition, all entities remain present and their total energy is preserved; only the temporal deviations of nonmembers are removed by replacing their actual profiles with their mean profiles. Therefore, the coalition scenarios differ only in the fluctuations retained and provide a common basis for comparing the marginal cost effects of different entities.

More generally, the temporal characteristics of multiple load entities may reinforce the downward regulation requirement during load valley periods. The cost of coalition $\{l_1, l_2, l_3\}$ is 488.51×10^4 CNY, compared with 253.07×10^4 CNY for $\{l_1, l_3\}$ and 201.20×10^4 CNY for $\{l_2, l_3\}$. This indicates that the combined fluctuations of the three load profiles create a stronger regulation requirement than the corresponding two load coalitions.

However, coalition cost does not increase monotonically with the number of entities because different profiles may exhibit temporal complementarity. The cost of coalition $\{v_1, l_1, l_2, l_3\}$ is 437.55×10^4 CNY, whereas adding PV power reduces the grand coalition cost to 147.17×10^4 CNY. This result indicates that the PV profile offsets part of the regulation requirement induced by the other entities. Therefore, installed capacity or total energy alone cannot represent coalition-specific cost effects, and the Shapley value is used to evaluate each entity according to its average marginal contribution across all coalitions.

4.2. Marginal Cost Assessment and Positive Contribution Settlement Results

The signed standard Shapley values and the final cost settlements obtained using the positive contribution rule are presented in Table 6.

Table 6. Signed Shapley marginal cost effects and positive contribution settlement results.

Peak Regulation Demand Entity	Signed Shapley Value (10 ⁴ CNY)	Signed Shapley Share	Final Allocation Share	Final Allocated Cost (10 ⁴ CNY)
v_1	15.94	10.83%	7.97%	11.73
v_2	−52.71	−35.82%	0%	0
l_1	93.66	63.64%	46.86%	68.96
l_2	50.34	34.20%	25.18%	37.06
l_3	39.94	27.14%	19.98%	29.41
total	147.17	100%	100%	147.17

As shown in Table 6, PV power has a signed Shapley value of -52.71×10^4 CNY, indicating that its actual output profile reduces the optimized deep peak regulation cost on average relative to the mean profile reference. Under the standard Shapley interpretation, this negative value may be regarded as a credit for its average cost-mitigating effect. However, the present study considers a one-sided cost recovery mechanism and does not introduce a separate subsidy fund. PV power is therefore exempted from this specific charge rather than receiving a direct payment. The resulting settlement is a positive contribution settlement rather than the standard Shapley allocation. An explicit reward for negative contributions would require separate market rules and a defined funding source.

The final charges are determined for the four positive contributors in proportion to their positive Shapley values. This positive contribution settlement produces nonnegative charges and ensures full recovery of the remunerated deep peak regulation cost. Residential load has the largest signed Shapley value, 93.66×10^4 CNY, followed by industrial load, commercial load, and wind power. After applying the positive contribution rule, residential load bears 68.96×10^4 CNY, accounting for 46.86% of the total remunerated cost. The corresponding final charges assigned to industrial load, commercial load, and wind power are 37.06×10^4 , 29.41×10^4 , and 11.73×10^4 CNY, respectively.

To provide a side-by-side comparison with alternative methods, the proposed settlement is compared with energy proportional and peak power proportional allocation. The former uses the total energy of each entity, whereas the latter uses its maximum hourly power. The maximum powers of wind power, PV power, residential load, industrial load, and commercial load are 3605.75, 3000.00, 7820.65, 11,783.26, and 8529.82 MW, respectively. All three methods recover the same total remunerated cost, as shown in Table 7.

Table 7. Comparison of settlement charges under different rules.

Peak Regulation Demand Entity	Energy Proportional Allocation (10 ⁴ CNY)	Peak Power Proportional Allocation (10 ⁴ CNY)	Proposed Settlement (10 ⁴ CNY)
v_1	13.97	15.28	11.73
v_2	4.55	12.71	0
l_1	34.10	33.13	68.96
l_2	64.96	49.92	37.06
l_3	29.59	36.14	29.41
total	147.17	147.17	147.17

The two benchmark methods allocate costs mainly according to participant scale and do not consider the timing or direction of power variations or their effects on the optimized system cost. Residential load is allocated 34.10×10^4 CNY and 33.13×10^4 CNY under the energy-proportional and peak-power-proportional methods, respectively, compared with 68.96×10^4 CNY under the proposed settlement. This difference arises because the

residential evening peak coincides with declining renewable output, thereby increasing net load variation and the requirement for deep peak regulation. The two scale-based rules therefore yield lower charges for residential load in this case. In contrast, although industrial load has the largest total energy and peak power, its relatively stable profile produces a smaller average marginal effect on the regulation cost. Its allocation under the proposed settlement is consequently 37.06×10^4 CNY, lower than the 64.96×10^4 CNY and 49.92×10^4 CNY obtained using the two benchmark methods. The benchmark rules also assign a positive charge to PV power according to its scale, whereas its negative Shapley value indicates that its temporal output profile reduces the deep peak regulation cost on average across the coalitions.

Accordingly, compared with the two proportional benchmarks, the proposed marginal cost-based settlement incorporates the timing, direction, and interaction of heterogeneous power profiles through coalition-specific re-optimization. This enables the method to distinguish cost-increasing and cost-mitigating profile effects and to determine final charges from the relative positive Shapley values derived from coalition-specific optimized cost changes. These results demonstrate a specific profile-sensitive cost attribution capability relative to the selected scale-based benchmarks.

4.3. Sensitivity Analysis of Key Parameters

To examine how the proposed settlement results change with operating conditions, two groups of sensitivity analyses were conducted. First, the wind power and PV power output profiles were scaled to evaluate the effects of renewable energy integration on their signed Shapley values and final settlement shares. Second, the thermal unit technical minimum output limits, pumped storage capacity, thermal deep regulation bids, and thermal ramp rate limits were varied to evaluate the effects of system flexibility and regulation prices on the total remunerated cost and the corresponding allocation results. For each parameter setting, all 32 coalition-specific dispatch problems were re-solved, followed by recalculation of the signed Shapley values and final settlements.

4.3.1. Sensitivity to Renewable Energy Integration Scale

The wind power and PV power output profiles were multiplied by different scaling factors. For each scenario, the coalition costs, standard Shapley values, and final cost shares were recalculated. The results are shown in Figures 7 and 8.

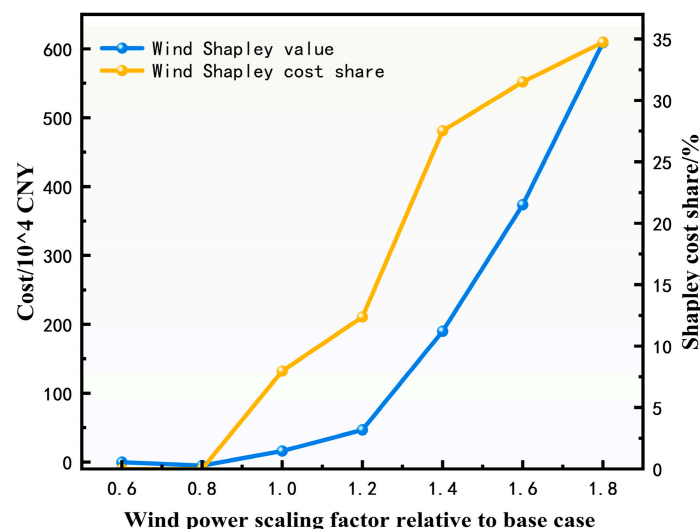


Figure 7. Influence of wind power ratio on peak regulation cost.

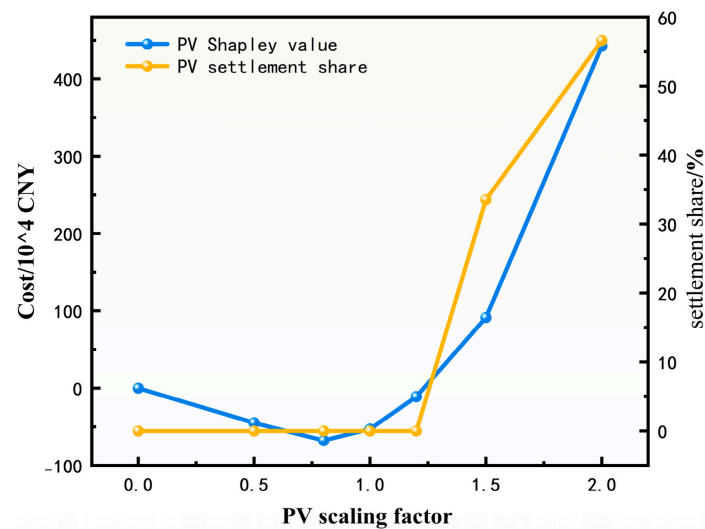


Figure 8. Influence of PV connection ratio on peak regulation cost.

As shown in Figure 7, both the standard Shapley value and final cost share of wind power generally increase with the output scaling factor. The increase becomes more pronounced when the scaling factor exceeds 1.4, and the final cost share exceeds 30% at a factor of 1.6. This indicates that large-scale wind power integration increases its average marginal effect on the system deep peak regulation cost. As shown in Figure 8, PV power exhibits a nonlinear response. At low and moderate scaling factors, its standard Shapley value is negative and its final cost share is therefore zero. When the scaling factor exceeds 1.5, the standard Shapley value becomes positive and increases rapidly. These results show that the cost effect of renewable generation depends not only on its energy scale but also on how its temporal output profile changes coalition-specific dispatch costs.

4.3.2. Sensitivity to Thermal Unit Flexibility and Deep Regulation Bids

In addition to the renewable energy integration scale, the total remunerated deep peak regulation cost and the corresponding allocation results are affected by physical flexibility and regulation prices. Therefore, the thermal unit technical minimum output limits, pumped storage capacity, thermal deep regulation bids, and thermal ramp rate limits were selected as representative sensitivity parameters.

Table 8 reports the effects of the physical flexibility parameters on the total remunerated cost. Table 9 further presents the allocation results under different thermal deep regulation bids and ramping capabilities.

Table 8. Effects of key parameters on the total remunerated deep peak regulation cost.

Parameter	Low Value	Cost (10 ⁴ CNY)	Base Value	Cost (10 ⁴ CNY)	High Value	Cost (10 ⁴ CNY)
Technical minimum output ratios (600/300/200 MW)	0.25/0.25/0.45	147.17	0.3/0.3/0.5	147.17	0.35/0.35/0.55	216.53
Pumped storage capacity (MW)	600	314.41	1200	147.17	1800	101.09
Thermal deep regulation bid (p.u.)	0.8	135.91	1.0	147.17	1.2	158.43

Table 9. Allocation sensitivity to thermal regulation price and ramping capability.

Parameter	Setting	Cost (10 ⁴ CNY)	Wind	PV	Residential	Industrial	Commercial
Thermal deep regulation bid (p.u.)	0.8	135.91	8.44%	0%	45.54%	25.54%	20.48%
	1.0	147.17	7.97%	0%	46.86%	25.19%	19.98%
	1.2	158.43	7.60%	0%	47.91%	24.90%	19.59%
Ramp availability factor	0.8	149.86	8.77%	0%	42.44%	27.23%	21.57%
	1.0	147.17	7.97%	0%	46.86%	25.19%	19.98%
	1.2	147.17	7.97%	0%	46.86%	25.19%	19.98%

As shown in Table 8, the remunerated deep peak regulation cost is highly sensitive to the physical flexibility of the system. When the technical minimum output ratios of the 600 MW, 300 MW, and 200 MW units are reduced from 0.30/0.30/0.50 to 0.25/0.25/0.45, the total cost remains 147.17×10^4 CNY, indicating that the corresponding lower output bounds are nonbinding in the base case optimum. By contrast, increasing the ratios to 0.35/0.35/0.55 contracts the feasible downward regulation range and raises the total cost to 216.53×10^4 CNY. Pumped storage capacity has an even stronger effect: reducing it from 1200 MW to 600 MW increases the total cost to 314.41×10^4 CNY, whereas increasing it to 1800 MW reduces the cost to 101.09×10^4 CNY. These results demonstrate that thermal minimum output capability and pumped storage capacity primarily affect the quantity of remunerated regulation that must be procured.

The thermal deep regulation bid mainly affects the economic valuation of the activated flexibility. A $\pm 20\%$ change in the bid results in total costs of 135.91×10^4 and 158.43×10^4 CNY. As further shown in Table 9, the residential load share varies only from 45.54% to 47.91% over the same bid range, although its allocated monetary cost increases with the bid. Residential load remains the largest positive contributor in all three cases. This indicates that its relatively high allocation is not an artifact of a particular thermal price assumption but is mainly attributable to the effect of its temporal profile on low net load periods, the activation depth of thermal regulation, and the resulting coalition-specific marginal costs. The ramping results provide an additional robustness test. Reducing the ramp availability factor from 1.0 to 0.8 increases the total cost from 147.17×10^4 CNY to 149.86×10^4 CNY and redistributes the settlement shares, because tighter intertemporal constraints alter the optimal dispatch costs of several coalitions. Nevertheless, residential load remains the largest positive contributor, PV retains a negative signed Shapley value and is therefore exempted from the final charge, and the ranking of the positive contributors remains unchanged. Increasing the ramp factor to 1.2 produces no further change, indicating that the ramp constraints cease to be cost-determining above the base flexibility level. Therefore, the proposed mechanism preserves its principal attribution pattern under moderate flexibility variations while remaining responsive when generation-side constraints become more restrictive.

These results show that the calculated coalition costs and settlements respond to changes in physical flexibility and regulation opportunity cost rather than being determined by fixed allocation coefficients. The sensitivity results are case-specific and do not constitute universal stability proof.

5. Conclusions

In response to the limitations of existing peak regulation cost allocation mechanisms in reflecting the cost responsibility of multiple participants, this study applies cooperative game theory to the deep peak regulation cost allocation problem involving multiple demand entities. The behavior of the proposed mechanism is evaluated through a provincial

system case study, benchmark comparisons, and parameter sensitivity analyses. The main conclusions are as follows:

(1) An energy-preserving substitute scenario method is used to construct coalition-specific net load profiles for residential load, industrial load, commercial load, wind power, and PV power. For each coalition, the deep peak regulation dispatch model is re-optimized while considering the piecewise regulation characteristics of thermal units and the intertemporal constraints of pumped storage. This procedure links the temporal profiles of heterogeneous entities to the corresponding optimized system costs.

(2) The signed standard Shapley value quantifies each entity's average marginal effect on the deep peak regulation cost across all coalitions. The positive contribution rule further converts these values into nonnegative and budget-balanced charges. Entities with negative Shapley values are exempted from payment, whereas the remunerated cost is recovered from entities with positive contributions.

(3) Compared with the energy and peak power proportional rules, the proposed settlement incorporates temporal profile effects and interactions among entities through coalition-specific re-optimization. In the case study, it identifies both cost-increasing and cost-mitigating effects and determines charges according to relative positive Shapley values. The sensitivity analyses further show that the settlement results change with renewable energy integration, system flexibility, and deep regulation prices. These findings demonstrate the profile-sensitive cost attribution capability of the proposed settlement under the selected case and benchmarks.

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