COST CAUSATION BASED ALLOCATIONS OF POWER REGULATION COSTS

Yan Meng*1,2, Shuai Fan1,2, Yi Zhang1,2, Guangyu He1,2

*1Department of Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China
1Shanghai Non-carbon Energy Conversion and Utilization Institute, Shanghai, China

Abstract

The proliferation of renewable energy (RE) and various inflexible loads (IL) exacerbate power variability, which poses great challenges to the system power regulation. Quantifying the regulation cost attributable to different types of generation and load is conducive to facilitating the permanent power regulation services. This paper proposes a cost allocation method of power regulation based on cost causation to quantify the regulation cost caused by system participants that may exacerbate power variability. First, the ideal scenario of RE and IL without power variations is constructed to serve as the baseline for calculating regulation cost. Subsequently, a comprehensive dispatch model considering deep peak regulation and demand-side dispatch is established to calculate the total operation cost of the system. The total regulation cost attributable to variability is obtained via calculating the cost difference between the actual dispatch and the ideal scenario. Finally, the Shapley value is leveraged to quantify the power regulation cost caused by each RE and IL participant. Simulation tests verify the effectiveness of the proposed method.

1 Introduction

Under the background of establishing new power systems, the installed wind power capacity has reached 370 GW with an 11.2% year-on-year growth and the installed solar power capacity has reached 390 GW with a 28.1% year-on-year growth in China by the end of 2022 [1]. The fluctuations of power output on all time scales, defined by NERC as variability [2], are exacerbated by the increasing penetration of renewable energy (RE). Besides, power consumption is also a large source of variability, such as the falcon curve of seasonal load fluctuations [3]. This paper discusses the variability on hourly level from the day-ahead perspective. As reported, the net load of California power grid has evolved from the duck curve to the canyon curve [4], which puts forward higher requirements of system flexibility to accommodate RE and ensure the power balance [5].

On the power generation side, thermal power units (TPUs) are the main resources to provide flexibility alleviate variability. In particular, they can provide flexibility via deep peak regulation (DPR), flexible ramping, and rapid startup and shutdown of units. Practice has proved that DPR is one of the most effective means to lighten power balance burden and facilitate RE accommodation [6]. An optimal scheduling model of TPUs was established based on the rules of China electricity ancillary services market to provide peak shaving and frequency regulation services [7]. Ref. [8] proposed a ladder-type ramp rate constrained DPR model with better consistency with engineering practice. The operation characteristics of basic peak regulation and DPR for TPUs are investigated and recommendations for the flexible transformation of TPUs are offered [9].

In terms of the demand side, with the sharp growth of distributed energy resources and flexible loads, the great potential for flexibility needs to be unlocked and utilized [10]. Virtual power plants (VPPs) play a significant role in alleviating variability by aggregating massive flexible resources on the demand side to shift power consumption to proper time of the day. A novel demand response mechanism was proposed via introducing network-constrained desired load profiles to guide customers like VPPs to provide flexibility [11]. A dynamic VPP algorithm considering electric vehicle clustering was presented with a better flexibility performance [12]. A market mechanism that can sufficiently incent VPPs to participate in power regulation was proposed, where energy shift vector was designed as a commodity for trading [13].

Though the existing literature has studied the optimal operation of power regulation involved both generation and demand sides, how to objectively allocate the regulation cost to form a stable funding pool to promote the permanent power regulation services remains to be addressed. Cost causation is a basic principle to follow when designing a cost allocation method which should satisfy: a participant inducing cost should pay for it with the amount of payment positively correlated with the degree of attribution [14]. Along this line, the cost of wind power variability was calculated via introducing an "equal-kwh following load" method to construct a scenario without wind variability [15]. Ref. [16] proposed a methodology to fairly allocate the variability cost of net load to the different classes of power generation and consumption. However, on the one hand, the participation of TPUs in DPR to provide flexibility is not considered in the calculation of regulation cost. On the other hand, the demand-side flexibility is neglected, that is, load is regarded as inflexible without capability of participating in power regulation via
shifting load. With the increasing burden of power regulation, DPR and demand-side flexibility are becoming paramount to address the power balance challenges in practice. The research gaps motivate the two-fold contributions:

1. **A comprehensive dispatch model considering DPR and VPP scheduling is proposed.** The fatigue life loss cost is introduced to characterize represent the economic loss caused by each participation in DPR of TPUs. The incentive function of demand scheduling for VPPs is designed from the perspective of contributions to variability alleviation. The ideal load profile of alleviating variability is taken as the tracking target of VPPs: the higher matching degree of VPPs with it, the more incentives VPPs gain.

2. **An allocation method of regulation cost is proposed, allocating fairly the regulation cost to different types of system participants including RE and inflexible load (IL) which cause variability.** The ideal scenario without power variations for RE and IL is established to serve as the baseline for calculating regulation cost. Then, the total regulation cost cause by variability is obtained by calculating the cost difference between the actual dispatch and the ideal scenario. At last, the regulation cost is allocated to RE and IL based on the Shapley value.

The remainder of this paper is organized as follows. Section II elaborates the cost allocation methodology including the construction of the ideal scenario without variability, the dispatch model, and the allocation method. Section III validates the performance of the proposed method via simulation tests. Section IV concludes the work.

2 Cost Allocation Methodology

2.1 Methodology overview

The cost causation principle-based cost allocation method originates from the accounting approach [17]. System participants are allocated with costs because they lead to costs. Traditionally, in the absence of uncertainty, system power regulation is aimed at mitigating fluctuations in the net load curve (load minus RE). However, the emergence of abundant demand-side flexible resources has endowed the load itself with a certain adjustable capability, allowing it to participate in power regulation. In light of this, this paper categorizes the load into IL and flexible load which is aggregated in the form of VPP to be directly dispatched by the system operator.

The power curve resulting from the superposition of RE (negative load) and IL should be balanced by TPUs and VPPs, which encompasses both energy balance and variability balance. Considering that RE and IL cause variability, we define them as the potential cost drivers, i.e., members that contribute to the cost of variability. Notably, potential cost drivers, as independent participants, may exacerbate variability in certain time periods while alleviating it in others. Evaluating their contributions to variability cost across the entire time span could overcome the limitations of existing methods that consider only a portion of the time. Intuitively, the difference in dispatch cost between the power profile with and without fluctuations for a single participant reflects the regulation cost attributed to it. However, the system-wide regulation cost results from the combined effects of all participants contributing to variability. In other words, the aforementioned difference in dispatch cost for that participant is influenced by other participants. To address this, we first construct an ideal scenario of the power profiles without fluctuations for potential cost drivers. Then, for each potential cost driver, the difference in dispatch cost is calculated across all possible scenarios composed of potential cost drivers with or without power fluctuations. Finally, the actual regulation cost attributed to each potential cost driver is obtained via weighting.

2.2 Ideal Scenario without variability

Let \( n \in D \) denote ILs with each IL output \( D_{n,t} \) and \( m \in R \) denote REs with each maximal output of \( RE_{m,t} \). With the assumption of constant total energy for, the corresponding power variations can be calculated:

\[
\Delta D_{n,t} = \frac{1}{T} \sum_{t \in T} D_{n,t} - \frac{1}{T} \sum_{t \in T} D_{n,t} \quad (1)
\]

\[
\Delta R_{m,t} = -\frac{1}{T} \sum_{t \in T} \frac{1}{T} \sum_{t \in T} R_{m,t} \quad (2)
\]

Note that RE output is considered as negative load when calculating its variations, as in (2). Let \( V = R \cup D \) be the sets of potential cost drivers. The power variations of each potential cost driver \( v \in V \) can be obtained:

\[
\Delta Q_{v,t} = \Delta D_{v,t} \quad \forall v \in D \]

\[
\Delta Q_{v,t} = -\Delta R_{v,t} \quad \forall v \in R \quad (3)
\]

Obviously, the power variation vector of \( v \) satisfies:

\[
\sum_{t \in T} \Delta Q_{v,t} = 0 \quad (4)
\]

The power curve with power variations \( Q \) that needs to be balanced by TPUs and VPPs and the ideal scenario without power variations \( \bar{Q} \) can be obtained:

\[
Q = \sum_{t \in T} \Delta D_{t} - \sum_{t \in T} R_{max} \quad (5)
\]

\[
\bar{Q} = \frac{1}{T} \left( \sum_{n \in D} \sum_{t \in T} D_{n,t} - \sum_{n \in R} \frac{1}{T} \sum_{t \in T} R_{m,t} \right) \quad (6)
\]

\[
\bar{Q} = Q - \sum_{n \in D} Q_{n,t} \quad (7)
\]

Equation (7) denotes the relationship between \( Q \) and \( \bar{Q} \), which can be easily proven via simple transformation. The variability can be expressed as \( Q - \bar{Q} \). The demand of power regulation is defined as the inverse variability:

\[
\Delta Q_{\text{max}} = -\sum_{n \in D} \Delta Q_{n,t} \quad (8)
\]

2.3 Dispatch model

The established dispatch model considers the regulation role of DPR of TPUs and VPPs. We categorize the output of TPUs into two stages: regulation peak regulation (RPR) and DPR, based on the operational state and energy consumption characteristics of TPUs. When the output falls below the DPR threshold, the unit enters DPR stage. In DPR stage, a certain fatigue life loss is incurred, and the corresponding cost increases with the decrease in the load ratio of TPUs. Note that DPR of TPUs can be further divided based on whether fuel oil is injected for combustion enhancement; however, this paper overlooks the fuel consumption cost associated with fuel oil injection.

Given that VPP possesses significant adjustment range in
its external power output, the conventional method of calculating baselines based on historical data and then calculating peak shaving is not well-suited for VPPs. Research indicates the closer the profile of the VPP power curve aligns with the ideal load curve that mitigates variability, the greater its contribution to system regulation [11]. Inspired by this insight, we adopt the demand of power regulation $\Delta Q_{\text{demand}}$ as the ideal load curve, enabling VPP's external power profile to follow the ideal load curve to a certain extent within its feasible range. The resulting incentive cost for a VPP is proportional to the similarity between these two curves.

Therefore, the objective (9) is minimizing the sum of TPU's operation cost (10), startup and shutdown cost (11), incentive cost of VPPs (12), and RE curtailment cost (13): 

$$
\min_{P_j, R_m, u, x, L, R} \sum_{i \in T} \left[ u_i f(P_i, j) + f_j(L_i) + f_j(R_m) \right] (9)
$$

$$
f_j(P_i) = \left[ c(P_i) + \mu_i C_{\text{loss}}^i + \beta_i C_{\text{in}}^i \right] P_j \leq P_{\text{max}}^i \leq P_{\text{min}}^i (10)
$$

$$
f_j(L_i) = e \cdot \left[ L_{\text{in}} - \Delta C_{\text{loss}}^i \right] (11)
$$

$$
f_j(R_m) = e \cdot \left[ R_{\text{in}} - \Delta C_{\text{loss}}^i \right] (13)
$$

Where $P_i$ denotes the generation of TPU $i, i \in G$ at time $t$; $L_i$ is the power consumption of VPP $j, j \in \mathbb{L}$; $R_m$ is the actual generation of RE $m$. $c(P_i)$ is the common quadratic function of generation $P_j$, $P_{\text{max}}^i$ denotes the DPR threshold of TPU $i$; the second term of $f_j$ in DPR stage is the fatigue life loss cost which is the product of actual operating loss coefficient $\mu_i$, fatigue loss coefficient $\beta_i$, and unit investment cost $C_{\text{in}}^i$, note that $\beta_i$ increases with increasing load ratio of TPU $i$. $u_i, y_i, z_i$ are the commitment status, startup index, shutdown index of TPU $i$ at time $t$, respectively; $C_{\text{in}}^i$ and $C_{\text{loss}}^i$ are the startup and shutdown cost of TPU $i$ at time $t$, respectively. In formula (12), $e$ is the incentive coefficient; the second product depicts the similarity between the demand of power regulation $\Delta Q_{\text{demand}}$ and variation curve of VPP power consumption $\Delta L_i$ as given in formula (14); both $\Delta L_i$ and $\Delta Q_{\text{demand}}$ are normalized by $l$-$1$ norm, as shown in (15). $\xi$ in (13) is the curtailment cost per unit of RE.

$$
\Delta L_{ij} = L_{ij} - \frac{1}{|T|} \sum_{t \in T} L_{ij} (14)
$$

$$
\Delta L_i = \frac{\Delta L_{ij}}{|T|} \sum_{t \in T} L_{ij} (15)
$$

$$
\Delta Q_{\text{demand}} = \frac{\Delta Q_{\text{demand}}}{\left| \Delta Q_{\text{demand}} \right|} (16)
$$

Constraints considered include:

$$
\sum_{i \in G} u_i P_i + \sum_{i \in G} R_m = \sum_{i \in G} L_i + \sum_{i \in G} D_{ij} (16)
$$

$$
\sum_{i \in G} u_i (P_{\text{max}}^i - P_{\text{ij}}) \geq P_{\text{RU}} (17)
$$

The system-level constraints represent the system power balance (16) and reserve requirement (17), respectively. $P_{\text{max}}^i$ and $P_{\text{min}}^i$ denote the maximal and minimal output of TPU $i$, respectively. $P_{\text{RU}}$ and $P_{\text{RD}}$ are the up and down reserve requirement value, respectively.

$$
\sum_{i \in G} u_i (P_{\text{max}}^i - P_{\text{ij}}) \leq u_i P_{\text{max}}^i (18)
$$

$$
P_{\text{ij}} - P_{\text{ij}} \leq \left[ 1 - u_i (1 - u_i) \right] P_{\text{RU}} + u_i (1 - u_i) P_{\text{RU, start}} (19)
$$

$$
P_{\text{ij}} - P_{\text{ij}} \leq \left[ 1 - u_i (1 - u_i) \right] P_{\text{RD}} + u_i (1 - u_i) P_{\text{RD, start}} (20)
$$

$$
y_i z_i = u_i - u_{i-1} \leq 1 (21)
$$

$$
y_i z_i + u_i \leq 1 (22)
$$

Constraints of TPU's represent the generation limits (18), ramping up and down limits (19)-(20), operating states constraints (21)-(22), minimum continuous OFF and ON time limits (23), $P_{\text{RU}}^i$, $P_{\text{RD}}^i$, $P_{\text{RU, start}}^i$, and $P_{\text{RD, start}}^i$ are maximal ramp-up and ramp-down rates, startup and shutdown rate limits, respectively. $X_{\text{off}}^i$, $X_{\text{on}}^i$, $T_{\text{on}}^i$, and $T_{\text{off}}^i$ are OFF and ON time of TPU $i$ at time $t-1$, minimum OFF and ON time of TPU $i$. 

$$
0 \leq R_{\text{max}}^i \leq P_{\text{max}}^i (24)
$$

$$
L_i \in \Omega_i (25)
$$

Constraints (24) represent the generation limits of RE. Constraints (25) denote the generalized operating limits of VPP $j$, where $\Omega_i$ is the VPP feasible domain.

### 2.4 Allocation method

When the power curve with power variations is $Q$ given, solving the proposed dispatch model yields the total system cost $F(Q)$. Similarly, for the case of no power variations, the system total cost can be obtained, denoted as $F(Q)$. Consequently, the regulation cost $V^i$ attributed to variability can be calculated:

$$
V^i = F(Q) - F(\bar{Q}) (26)
$$

For a potential cost driver $v$, the regulation cost attributed to it in a scenario composed of potential cost drivers with or without power variations is denoted by the difference in dispatch cost between its power curve with and without variations.

$$
M_v(\mathcal{V}) = F(\bar{Q}) + \sum_{i \in \mathcal{V}} \Delta Q_i - F(\bar{Q}) - \sum_{i \in \mathcal{V}} \Delta Q_i (27)
$$

$M_v(\mathcal{V})$ denotes the regulation cost caused by $v$ in a scenario where the participants belonging to $\mathcal{V} (v \in \mathcal{V}, \mathcal{V} \subseteq \mathcal{V})$ are with power variations, while the others are without power variation.

The Shapley value in cooperative game theory is widely deemed as an equitable method for allocating the total cost [18]. It effectively characterizes the weighted average cost of each potential cost driver in scenarios where mutual influence among cost drivers exists. Therefore, the Shapley value is leveraged to calculate the weighted average of regulation cost $\psi_v$ attributed to the potential cost driver $v$ across all scenarios:

$$
\psi_v = \frac{1}{|\mathcal{V}|} \sum_{i \in \mathcal{V}} \frac{M_v(\mathcal{V})}{\left| \mathcal{V} \right|} (28)
$$
\[ \Psi_v = \sum_{V \subseteq V} M_v(V') \left( \left| V' \right| - 1 \right) \frac{\left| V \right| - \left| V' \right|}{\left| V \right|} \]  

(28)

Based on the properties of the Shapley value, the following relationship can be derived:

\[ \sum_{v \in V} \psi_v = F^v \]  

(29)

The obtained weighted average regulation cost of each potential cost driver reflects its average contribution to the total system regulation cost. It can be inferred that the weighted average regulation cost of some potential cost drivers might be negative, indicating that they, relative to their absence of power variations, contribute to the system regulation. Hence, they are excluded from the allocation of regulation costs. The regulation cost allocation factor \( A_v \) for each potential cost driver is calculated as:

\[ A_v = \frac{\text{ReLU}(\psi_v)}{\sum_{v \in V} \text{ReLU}(\psi_v)} \]  

(30)

3 Simulation Results and Discussion

3.1 Simulation setup

3.2 Power variability

![Power curves with and without variations of potential cost drivers. (a) Wind power. (b) Solar power. (c) Inflexible load 1. (d) Inflexible load 2. (e) Inflexible load 3. (f) Total power curve to be balanced.](image)

A system consisting of two TPUs, one wind generation, one solar generation, three ILs, and two VPPs is adopted to validate the effectiveness of the proposed method. The operating parameters and RPR cost of TPUs come from [19], while the profiles RE and IL are obtained from Elia [20]. For DPR stage of TPUs, the actual operating loss coefficient is set to 1.2. The investment costs are 627 $/kW and 520 $/kW for TPU1 and TPU2, respectively. The values of the fatigue loss coefficient, varying with the load ratio of TPU, are presented in Table 1.

<table>
<thead>
<tr>
<th>TPU Load Ratio (%)</th>
<th>30–27.5</th>
<th>27.5–25</th>
<th>25–22.5</th>
<th>22.5–20</th>
<th>20–17.5</th>
<th>17.5–15</th>
<th>15–12.5</th>
<th>12.5–10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load ratio (%)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Fatigue loss coeff.</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>13</td>
<td>16</td>
<td>17</td>
<td>19</td>
<td>22</td>
</tr>
</tbody>
</table>

![Fig. 1. Power curves with and without variations of potential cost drivers.](image)

Fig. 1. Power curves with and without variations of potential cost drivers. (a) Wind power. (b) Solar power. (c) Inflexible load 1. (d) Inflexible load 2. (e) Inflexible load 3. (f) Total power curve to be balanced.

![Fig. 2. Dispatching results of different resources.](image)

Fig. 2. Dispatching results of different resources. (a) Ideal scenario with no variability. (b) Actual dispatch...
Fig. 2 presents the dispatch results of the ideal scenario without power variations and the actual scenario. In the ideal scenario, both IL and RE exhibit no power variations, indicating that no variability exits. Consequently, apart from the initial time periods where TPUs experience power variations due to prescheduling status constraints, the power profiles of TPUs and VPPs remain nearly flat. In contrast, in the actual scenario, the noon-to-afternoon-hour decrease in IL consumption and the increase in RE generation compel TPUs to decrease their output for power balance. Evidently, during 11-18h for TPU1 and 12-16h for TPU2, TPU output falls below the corresponding DPR thresholds, indicating that they enter the DPR stage, consequently incurring associated fatigue life loss costs. For VPPs, the dispatch outcomes show that they effectively introduce positive power consumption variations, thereby partially mitigating variability during noon to afternoon hours. The dispatch results of the two VPPs present distinct trends in their power profiles in some periods, such as 17-19h. The differences are primarily attributed to the feasible domain constraints specific to each VPP. In summary, the variability induced by IL and RE is effectively mitigated through the dispatch of TPUs and VPPs, so that power balance is ensured at every moment.

![Power dispatch comparison](image)

Fig. 3. Power of VPPs after dispatch. (a) VPP1. (2) VPP2.

### 3.4 Allocation of regulation cost

![Cost allocation](image)

Fig. 4. Total system cost under different scenarios of variability.

Note: scenarios of variability are represented via 5-bit binary sequences "b1b2b3b4b5", where \( b_i \) correspond to the wind, solar, IL1, IL2, and IL3, respectively. \( b_i = 1 \) indicates the presence of power variations for element \( v \) in the corresponding scenario, while \( b_i = 0 \) for no variations of \( v \). The combination of five elements results in 32 possible permutations. The horizontal axis corresponds to the decimal values of the binary sequences.

![Total system cost](image)

Fig. 4 depicts the total system cost under different scenarios of variability. The sum of regulation costs in Fig. 5 is equal to the difference between the cost in scenario "11111" (31) and scenario "00000" (0) in Fig. 4, i.e., the total regulation cost of $2672.55, which satisfies the Equation (29). Furthermore, it can be observed that transitioning from scenario "00111" (7) to scenario "01000" (8) results in a considerable increase in system cost, indicating that the regulation burden of the system in the scenario with only solar variations is significantly intensified than that in the scenario with only variations of IL. This observation underscores the solar generation as a significant contributor to variability in the test system.

Fig. 5 presents the weighted average regulation cost attributed to potential cost drivers. In Fig. 6, the cost allocation coefficients are depicted. The solar induces the highest regulation cost, accompanied by the largest corresponding allocation coefficient. It is because that a significant portion of variability originates from the solar power profile, as discussed in Subsection B. IL1 and wind power contribute to some extent to regulation costs, as they are also the sources of variability. Due to its minor variations, IL3 incurs the least regulation costs and features the smallest allocation coefficient. Notably, IL2 exhibits a negative cost, implying its favorable impact on the system regulation, thus exempting it from cost allocation. This aligns with the phenomenon where its power variations oppose the trend of variability. Therefore, the allocation coefficients effectively reflect the extent to which potential cost drivers cause regulation costs. The proposed method well adheres to the cost causation principle.

![Cost allocation](image)

Fig. 5. Weighted average regulation cost of RE and IL.

![Allocation factor](image)

Fig. 6. Allocation factor of regulation cost.
4 Conclusion

From the perspective of variations of renewable energy (RE) and inflexible load (IL) power curves across the entire time span, this paper proposes a cost causation-based allocation method of regulation cost in the day-ahead scheduling considering deep peak regulation of thermal power units and demand-side virtual power plants dispatch. The test results demonstrate that the weighted average regulation cost of RE and IL effectively reflects their respective contributions to the system regulation burden. The proposed method fairly allocates regulation costs to the potential cost drivers causing power variability, facilitating the establishment of a stable funding pool to promote the permanent provisions of regulation services.

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6 References


