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A bi-level scheduling model for virtual power plants with aggregated thermostatically controlled loads and renewable energy

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HIGHLIGHTS

- Thermostatically controlled loads are scheduled to decrease imbalanced power of virtual power plant.
- Proportion static and dynamic aggregation not affected by parameters heterogeneity are proposed.
- A bi-level optimal scheduling model and its two-step simplified algorithm are established.
- The performance is verified under different regulating ranges, heterogeneity and forecast errors.

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ABSTRACT

With the penetration of renewable energy increasing, the power system requires higher flexibility of power regulation. Virtual power plants can aggregate distributed flexible loads to improve the utilization of distributed renewable energy. In this paper, a bi-level scheduling model for virtual power plants with a large number of distributed thermostatically controlled loads and intermittent renewable energy is established to reduce the net exchange power deviation caused by the forecast error of renewable energy. The upper level optimizes the exchange power curve and reduces the imbalance costs in intraday, while the lower level tracks the optimized power curve in real-time to complete the regulation target. Static and dynamic aggregation method reflecting the regulation characteristics of aggregated thermostatically controlled loads is proposed and applied in lower/upper level, respectively. In addition, a two-step simplified strategy is proposed to solve the mixed integer nonlinear programming in upper level. Simulation results show that the proposed method can reduce the maximum imbalance power, and it is not affected by parameters heterogeneity, which is suitable for virtual power plants with diversified users.

1. Introduction

With the rapid depletion of fossil fuels, developing renewable energy sources (RES) such as photovoltaic generation (PV) and wind power has become a trend of energy revolution. However, the uncertainty of RES output may lead to power imbalance and increase the power regulating burden [1]. RESs are integrated into power system either in a centralized way or a distributed way. In the centralized way, the stochastic model is often used to model and schedule the large-scale power plants [2,3]; while in the distributed way, with the characteristics such as small capacity, large number and wide distribution region, distributed RESs are difficult to be directly dispatched one by one. Therefore, virtual power plant (VPP) is proposed to coordinate these distributed RESs. With advanced measurement, communication and other technologies, VPP aggregates distributed energy resources (DER) including distributed generations (DG), energy storage systems (ESS) and flexible loads (FL), and then take part in the operation of the power system as an agent [4]. VPP can coordinate each regional controllable object to utilize distributed renewable energy locally, or provide ancillary services for centralized renewable energy power plants.

1.1. Optimal operation for VPP

Nowadays, VPP has been studied in many literatures, and the RESs are always contained to improve the economic efficiency and environmental benefit.

Some focus on the cooperation between various DERs. Ref. [5] offering an optimal operation for VPP with RESs, ESSs and conventional

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Nomenclature

Matrix

$\mathbf{P}_t^{static}$	static power regulation characteristic of cluster TCLs
$\mathbf{P}_{c,t}^{dynamic}$	dynamic power regulation characteristic of an individual TCL
$\mathbf{P}_t^{dynamic}$	dynamic power regulation characteristic of cluster TCLs
$\mathbf{U}_t$	sequence of the threshold value $u_{c,t}^*$
$\mathbf{C}$	set of the users in VPP
$\boldsymbol{I}$	set of $I_{i,j,t}$ in each intraday optimization

Indices

c	user index, $c = 1,2,\ldots,N_{cus}$
i	longitudinal index in the interpolation, $i = 1,2,\ldots, N_{tes1}$
j	transverse index in the interpolation, $j = 1,2,\ldots, N_{tes2}$
k	iteration times of Step 2, $k = 0,1,\ldots, k^{\max}$
t, τ	time index, $t = 1,2,\ldots,T$, $\tau \le t$

Parameters

$k^{\max}$	maximum iteration times of Step 2
$K_{i,j,t}^X$, $K_{i,j,t}^Y$	slope of each longitudinal/transverse segments
$KK_{i,j,t}^{XY}$	second order partial derivative in lookup table
N_{cus}	number of customers in VPP
N_{tes1},N_{tes2}	number of discrete points of dynamic aggregation
P_c^{rate}	rated power of an individual HVAC
P_t^{basic}	basic loads excluding TCLs
$P_t^{net,ahead}$	VPP day-ahead planned trading curve
$P_t^{PV,intra}$	total intraday forecast power of PVs
$T_c^{in,\min}$	minimum allowable indoor temperature
$T_c^{in,\max}$	maximum allowable indoor temperature
$T_{c,t}^{out}$	outdoor ambient temperature
T_c^{db}	temperature dead band
$u_{c,t}^*$	on/off boundary of an individual HVAC
ρ_e^{up},ρ_e^{down}	upward/downward imbalance energy price
ρ_c^{up},ρ_c^{down}	upward/downward imbalance capacity price
$\sigma_{i,t}^{\max}$,$\delta_{j,t}^{\max}$	maximum length of each longitudinal/transverse segments

Variables

$I_{i,j,t}$	binary lookup table auxiliary 0–1 variable
SU_t	accumulative proportion regulation signal
P_t^{target}	target power of real-time power tracking
$P_{c,t}^{HVAC}$	electric power of an individual HVAC
P_t^{TCL}	total power demand of TCLs
P_t^{net}	net exchange power between VPP and the power gird
$T_{c,t}^{in}$	user's room temperature
$T_{c,t}^{set}$	indoor temperature set point
$\Delta T_{c,t}$	temperature set point change
u_t	proportion regulation signal
$Z_{c,t}$	on/off status of HVAC system
$\sigma_{i,j,t}$,$\delta_{i,j,t}$	longitudinal/transverse segments variable.

ETP Parameters

$\overline{P}^{rate}$	typical rated power of HVACs
$\overline{COP}$	typical efficiency of HVACs
$\overline{R}$	typical thermal resistance
$\overline{C}$	typical heat capacity

power plants in both day-ahead and balance markets. Refs. [6–8] conducts day-ahead scheduling for an electricity-thermodynamics coupled VPP. Ref. [9] proposes a forecast method for RESs based on meteorological data to guide the output of other units. Ref. [10] focuses on industrial VPP and tests its performance under different kinds of demand response (DR) programs. Ref. [11] identifies the operation of price-based DR in VPP day-ahead dispatch, and the incentive-based DR is further applied in intraday. Ref. [12] takes the coordinated operation of electricity and natural gas networks base on VPP.

On the other hand, the bidding strategies of commercial VPP in electricity market are also discussed. Ref. [13] provides an optimal bidding strategy including the VPP benefit maximization and the day-ahead market clearing. Ref. [14] provides a non-equilibrium bidding strategy for VPP based on deterministic price-based unit commitment. Ref. [15] proposes a profit allocation framework with less calculation work.

Most of the above literatures make use of flexible loads to deal with the forecast error of RESs [7–15], and some further consider VPP providing multiple services [5,7,11,14,15]. Luckily, relatively complete theories about VPP day-ahead optimization has been developed, but they need to be further corrected by intraday rolling optimization and verified by real-time power tracking. Besides, their work is based on the premises that the aggregated regulation characteristic of distributed flexible loads is known, which is not easy to obtain directly in practice. Therefore, the regulation model and aggregation method of distributed flexible loads are needed.

1.2. Model and aggregation for distributed flexible loads

As for modeling the distributed flexible loads in VPP, many scholars focus on the analysis of thermostatically controlled loads (TCL) due to their great power regulation potential, and much related work have been launched.

First, there are kinds of accurate models for an individual thermostatically controlled system: For example, Ref. [16] uses the thermal mass of a building to defer power consumption from electric space heating; Ref. [17] establishes a high-order differential thermostatically controlled model for large buildings; Ref. [18] deems TCLs as virtual ESS to help micro-grids to consume distributed renewable energy; Ref. [19] presents a practical case of a modern non-residential building with controllable heating, ventilation and air-conditioning system (HVAC). Refs. [16–19] offer a HVAC model for a building. But for VPP consisting of residential TCLs with small capacity, the contribution that an individual user can make to power system is minimal. Therefore, a load aggregation program should be applied to make total capacity large enough, so that their effect of DR can be fully developed.

Second, based on this motivation, some research about the aggregation of distributed TCLs has been carried out. For example, Ref. [20] proposes a framework where TCLs provides ancillary services to power grid under direct load control. Ref. [21] builds models for HVACs in EnergyPlus, and calculates their aggregated power regulation capacity. Ref. [22] constructs the power density function for both the active and inactive machine-states of TCLs in real-time. Ref. [23] describes the state of air conditioners by means of the temperature priority list. Based on the demand bidding curve, Ref. [24] aggregates response capabilities of smart homes. The above literatures quantitatively analyze the regulation capacity of TCLs, but they just evaluate the performance of TCLs in a certain time section and make load control decisions step by step, which is referred as the "static" control in this paper. However, the thermodynamic model of TCL is usually described as differential equations of temperature versus time, which means the regulation between each time section influences others. Hence, because the optimization period contains more than one time section in day-ahead and intraday optimization, it is necessary to establish a "dynamic"