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Optimal dispatch of virtual power plant using interval and deterministic combined optimization

Yangyang Liu[a,*], Min Li[a], Hongbo Lian[a], Xiaowei Tang[a], Chuanquan Liu[a], Chuanwen Jiang[b]

[a] State Grid Shanghai Municipal Electric Power Company, Shanghai 201699, China
[b] Department of Electrical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

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ABSTRACT

Virtual power plant (VPP) technology is a promising solution to manage the uncertainties of renewable energy in demand side. Because of various uncertainties, VPPs' dispatch models are always solved by stochastic optimization, robust optimization and interval optimization. However, these approaches always require high computational complexity, be over conservative or cannot describe VPPs' profitability precisely. Thus, this paper combined interval and deterministic optimization together and adopted the combined approach to solve a VPP's dispatch problem. The combined optimization not only maximized VPPs' deterministic profits under forecasted scenarios to estimate the VPP's most likely profits, but also maximized VPPs' profit intervals to manage uncertainties. The proposed model was in a regulated electricity market environment, and the VPP's traded energy was cleared by time-of-use prices. A case study from real world was adopted to prove the validity of this model. Comparison with other optimizations like stochastic and robust optimization was also studied. The combined optimization can manage the VPP's uncertainties within limited computational time.

Nomenclature

A. Indexes

L	indicator of the left limit of the interval
R	indicator of the right limit of the interval
s	index for scenarios
t	index of time periods

B. Constants

$\boldsymbol{A}/\boldsymbol{B}$	interval numbers
$a/b/\lambda$	real numbers
$a_f/b_f/a_h/b_h$	CHP unit's characteristic parameters
$\mathrm{eff}_{bat,c}/\mathrm{eff}_{bat,dc}$	efficiency of storages' charging/discharging
eff_{bl}	efficiency of boiler
eff_{ev}	efficiency of EV charging
$L^{s,t}$	local load demands
$[L^L,L^R]$	intervals of local load demands
$O_{bat}^{s,t}$	operating and maintenance costs of storages
$P_{chp}^{min}/P_{chp}^{max}$	CHP unit's minimum/maximum outputs
P_{ev}^{max}	EVs' maximum charging power
$P_{pva}^{s,t}/P_{wa}^{s,t}$	available wind/solar power
Q_{gas}	natural gas prices
Rp_{up}/Rp_{dw}	CHP unit's ramp up/down speed limits
S_{up}/S_{dw}	CHP unit's start up/shut down ramp speed limits
$SoC_{bat}^{min}/SoC_{bat}^{max}$	storages' minimum/maximum state of charge
SoC_{bat}^{end}	storages' terminal state of charge requirement
$SoC_{ev}^{s,t}$	state of charge of EVs' battery
SoC_{ev}^{max}	maximum value of EV batteries' state of charge
SoC_{ev}^{end}	terminal requirement of EV batteries' state of charge
$[T_{bl}^{min}/T_{bl}^{max}]$	minimum/maximum value of boiler outputs
Tev	terminal hour for EV charging
$[T_d^L,T_d^R]$	thermal demand intervals
$T_d^{s,t}$	thermal demands
$\mathrm{w}(\mathbf{A})/\mathrm{m}(\mathbf{A})$	width and midpoint of interval A
y	vectors of random variables
Y	set of all possible random variables
$Z_{bat}/Z_{p,chp}$ $/Z_{t,chp}/Z_{pv}$	operating and maintenance cost per unit output of storage units/CHP power/CHP thermal/solar

* Corresponding author.
E-mail addresses: lyy_liu@163.com (Y. Liu), cqliu_whu@163.com (M. Li), lianhb@163.com (H. Lian), tenortxw@126.com (X. Tang), 7289281@qq.com (C. Liu), jiangcw@sjtu.edu.cn (C. Jiang).

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$/Z_w/Z_{bl}$ power/wind power/boiler
β deterministic factor in multi-objective problem
$\delta_{sell}^{t}/\delta_{sell}^{t}$ time-of-use prices for selling/purchasing energy to/from the main grid
δ_{dev} penalty price for exchanged energy deviation
δ_{shed} penalty price for shed load
ξ DM's degree of pessimism

C. Variables

$C_{fuel}^{s,t}$ VPP's total fuel costs
$C_{OM}^{s,t}$ VPP's total operating and maintenance costs
$F_{chp}^{s,t}/F_{bl}^{s,t}$ fuel consumption of CHP unit/boiler
$I_{chp}^{s,t}$ states of CHP, 1 means operation, 0 otherwise
$L_{ev}^{s,t}$ EVs' charging power
$\mathbf{P}$ the possible profit interval of the VPP
P^{d} the VPPs' most likely profits under random variables' forecasted value
$P_{buy}^{s,t}$ energy purchased from the distribution company
$P_{bat}^{s,t}$ storage units' outputs
$P_{bat,c}^{s,t}/P_{bat,dc}^{s,t}$ storage units' charing/discharging power
$P_{bat}^{\max}$ storage units' maximum outputs
$P_{chp}^{s,t}$ CHP unit's outputs
$P_{cut}^{s,t}$ renewable power curtailment
$[P_{DG}^{L},P_{DG}^{R}]$ intervals of DGs' outputs
P_{g}^{L} trading energy with the main grid
$P_{g}^{plan,t}$ planned trading energy schedule
$[P_{g}^{L},P_{g}^{R}]$ intervals of trading energy
$P_{sell}^{s,t}$ energy sold to the distribution company
$P_{dev}^{s,t}$ deviation of exchanged energy
$P_{shed}^{s,t}$ shed load
$[P_{shed}^{L},P_{shed}^{R}]$ intervals of shed load
$pen^{s,t}$ penalty of deviation and load shedding
R_{vpp}^{d} VPP's deterministic profits
$[R_{vpp}^{L},R_{vpp}^{R}]$ VPP's profit intervals
$SoC_{bat}^{s,t}$ storage units' state of charge
$T_{bl}^{s,t}$ boiler's thermal outputs
$T_{chp}^{s,t}$ CHP unit's thermal outputs
$[T_{DG}^{L},T_{DG}^{R}]$ DGs' thermal output intervals
$[T_{dis}^{L},T_{dis}^{R}]$ intervals of dissipated thermal power
$T_{dis}^{s,t}$ dissipated thermal power
x_d day-ahead decisions
x_r real time decisions
y_0 random variables' forecasted values
y_{chp}^{t} start up indictor, 1 means start up operation, 0 otherwise
$\overline{y}$ random variables in best situation
$\underline{y}$ random variables in worst situation
z_{chp}^{t} shut down indictor, 1 means shut down operation, 0 otherwise

D. Functions

$h(\cdot)$ equality constraints
$g(\cdot)$ inequality constraints
$Pr(\cdot)$ probability estimation function

Remark: All bold letters denote interval numbers in this paper.

1. Introduction

More and more renewable energy sources have been integrated into power systems in the form of distributed generations (DGs). They can support distribution network operation and provide clean energy, but they are difficult to control [1]. Thus, the virtual power plant (VPP) technology has attracted broad attentions as a feasible solution to control DGs. The VPP combines the separately located DGs by communication technology and centrally dispatchs them by energy management systems [2]. The VPP can reduce DGs' generation uncertainties, reduce deviation losses and increase total profits [3].

Ref. [4] proposed a dispatch strategy for VPPs under the time-of-use (TOU) pricing. Combined heat and power (CHP) units were considered in Refs. [3,5], the profits from electricity generation and heat supply were optimized. Ref. [6] established a dispatch model for VPPs with electric vehicles (EVs). In Ref. [7], the customers' satisfaction, system stability and so on were optimized by a fuzzy multi-objective optimization problem. All of the references above were based on random variables' forecasted values using deterministic optimization. Since load demands and renewable power cannot be predicted precisely, VPPs' actual profits may deviate from the optimized results, and these deviations may result in unexpectable losses.

In order to handle the uncertainties in the VPPs' dispatch problem, various uncertainty modeling methods, such as probabilistic method and nonparametric methods, have been proposed [8]. Decision makers (DMs) can choose the suitable method according to the available information of random variables. Stochastic optimization is a widely employed probabilistic method in many references' dispatch models to manage uncertainties. To maximize the VPP's expected profit, bidding strategies for the coordination of wind and hydro power were proposed by [9]. To measure the unfavorable effects of uncertainties, some risk indexes have been proposed and considered in the stochastic optimization. The risk measure, conditional value at risk (CVaR), was often optimized with the expected profits, and they formed multi-objective optimizations [10,11]. Considering the tradeoff between profit and risk, risk adjusted return on capital was introduced in the VPP's bidding strategy as a objective [12]. Besides, two popular risk measures,first-order stochastic dominance constraints and second-order stochastic dominance constraints, were also introduced to the VPPs' dispatch problems [13,14].

However, probabilistic method needs random variables' exact probability distributions which are hard to estimate exactly. Thus, nonparametric methods like fuzzy optimization,robust optimization, information gap decision theory (IGDT) method and interval optimization are often employed in recent years. In fuzzy optimization, membership functions are adopted to measure the preferences of random variables [15]. IGDT method maximizes the VPPs' tolerance of uncertainties to ensure acceptable profits [16]. Robust optimization obtains conservative schedules and maximizes the worst profits that the VPP may suffer [17,18]. Robust optimization focuses on VPPs' worst profits and loses sight of the whole possible range of profits. Thus, its schedule cannot be as profitable as other optimization approaches most of the time. Compared with robust optimization, interval optimization considers not only the worst cases but also the best cases, and it optimizes VPPs' whole profit intervals. Ref. [19] proposed a dispatch model for the unit commitment problem using intervals to represent net load uncertainties. Considering wind power integration, stochastic optimization and interval optimization were compared in a security-constrained unit commitment problem [20]. Ref. [21] adopted a preference ordering from a pessimistic DM's point of view for interval numbers and optimized the total profit intervals of generating companies (GENCOs). However, interval optimization cannot figured out GENCOs' expected profits or most likely profits, and the optimal intervals' ranges are always too wide to describe GENCOs' profitability precisely. Nonparametric optimization approaches do not require the whole information on random variables, and they can only provide limited information on VPP's profits. Thus, DMs may still blind to VPPs' profitability. Deterministic optimization may be a good choice to cooperate with nonparametric optimization. It figures out the VPP's most likely profit,