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Operational planning and optimal sizing of microgrid considering multi-scale wind uncertainty

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HIGHLIGHTS

- A microgrid is managed by considering dynamic and uncertain nature of the system.
- 2SSP for a day operation is combined with a day-to-day MDP for temporal connection.
- Size of the system component is optimized based on the value function for the MDP.
- A multi-scale wind model is developed for integration of the decision hierarchy.
- The proposed method is examined for a benchmark case study with real wind data.

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ABSTRACT

Distributed and on-site energy generation and distribution systems employing renewable energy sources and energy storage devices (referred to as *microgrids*) have been proposed as a new design approach to meet our energy needs more reliably and with lower carbon footprint. Management of such a system is a multi-scale decision-making problem encompassing hourly dispatch, daily unit commitment (UC), and yearly sizing for which efficient formulations and solution algorithms are lacking thus far. Its dynamic nature and high uncertainty are additional factors in limiting efficient and reliable operation. In this study, two-stage stochastic programming (2SSP) for day-ahead UC and dispatch decisions is combined with a Markov decision process (MDP) evolving at a daily timescale. The one-day operation model is integrated with the MDP by using the value of a state of commitment and battery at the end of a day to ensure longer term implications of the decisions within the day are considered. In the MDP formulation, capturing daily evolving exogenous information, the value function is recursively approximated with sampled observations estimated from the daily 2SSP model. With this value function capturing all future operating costs, optimal sizing of the wind farm and battery devices is determined based on a surrogate function optimization. Meanwhile, a multi-scale wind model consistent from seasonal to hourly is developed for the connection of the decision hierarchy across the scales. The results of the proposed integrated approach are compared to those of the daily independent 2SSP model through a case study and real wind data.

1. Introduction

An energy system (referred to as 'grid') has to be managed for stable and efficient generation and distribution. A new concept has emerged recently, the *smart grid*, which is an intelligent energy grid system including a variety of advanced energy supplier/customer such as renewable energy resources, smart meters, and electric cars with improved efficiency by integrating with ICT along the entire energy supply networks. As the infrastructure of grid becomes more advanced in terms of energy generation, information sharing/management, and communication with complex and fully integrated network, smart management applications and services should keep pace with it in order to achieve the objectives related to supply and demand balance, operation cost reduction, and utility maximization [1,2]. However, the smart grid management in its essence is a stochastic dynamic optimization problem having a multi-time scale, multi-period decision horizon and high uncertainty, for which efficient mathematical problem formulations and solution algorithms are lacking thus far.

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Nomenclature

Indices/Sets

d	index for days
D_m	set of days in month m
g	generators
G	set of generators
G^s	set of slow-start generators
h	hours
H	set of daily hours
H_{uc}	set of unit commitment decision epochs
k	energy dispatch sources
K	set of energy dispatch sources containing producing from generators, charging/dis-charging battery, buying/selling, which is defined by {G, ch, $disch$, buy, $sell$}
n	iterative numbers for the value function approximation
N	the number of iterations for the value function approximation
m	months
M	set of months
t	multi-scale time index which is defined by (m, d, h) (or just simplified h in the one-day operation model)
$\mathrm{A}_{m,h}$	set of the wind model parameters related to the hourly variation for month m
E_m	set of the wind model parameters related to the inter-day variation for month m
ω	intraday wind scenarios
$\Omega^{\alpha}_{m,d}$	set of intraday wind scenarios realized in time (m, d)
Ω^{ε}_{m}	discrete space of daily average wind values for month m

Parameters

$B_{\min}$	lower limit of battery state
$B_{\max}$	upper limit of battery state
C^g_U	unit start-up cost of generator g
C^g_D	unit shut-down cost of generator g
C^g_S	unit setup cost of generator g
$C_{disp,k}$	unit dispatch cost of source k
C_{lost}	unit penalty cost of lost-demand
C^w_{capa}	unit investment cost for capacity acquisition of wind plant
C^b_{capa}	unit investment cost for capacity acquisition of battery
$e^{\min}_{m,h}$	lower bound of hourly random noise in the intraday wind model for month m
$e^{\max}_{m,h}$	upper bound of hourly random noise in the intraday wind model for month m
MT	minimum up/down time limitation of fuel-based generators
$P^k_{\min}$	lower limit of dispatch source k
$P^k_{\max}$	upper limit of dispatch source k
P^w_r	rated electrical power in the wind conversion model
R^g_{down}	hourly ramp-up limit of generator g
R^g_{up}	hourly ramp-down limit of generator g
w_c	cut-in wind speed in the wind conversion model
w_r	rated wind speed in the wind conversion model
w_f	cut-off wind speed in the wind conversion model
$\beta^{WIND}_{m,h}$	vector of parameters in the intraday wind model for month m hour h
$\beta^{h}_{m,h}$	wind model parameter denoting the bias of daily-hour for month m hour h
$\beta^{d}_{m,h}$	wind model parameter denoting the effect of daily-average for month m hour h
$\beta^{h-1}_{m,h}$	wind model parameter denoting the effect of previous hour for month m hour h
$\beta^{SR}_{m,\cdot}$	vector of parameters in the surrogate value function for month m
γ	discount factor for the value function approximation
η_{ch}	charging efficiency of battery
θ^n_m	n-th iterated coefficient vector of the value function for month m
$\mu^e_{m,h}$	hourly mean value of random noise in the intraday wind model for month m
$\pi^{\alpha}_{m,d}$	probability of intraday wind scenario realized in time (m, d)
π^{ε}_m	state transition probability of daily average wind value for month m
σ^b	self-discharging rate of battery
$\sigma^e_{m,h}$	hourly standard deviation of random noise in the intraday wind model for month m

Variables

b^{ω}_t	battery level in time t given scenario ω
c_w	capacity of wind generators
c_b	capacity of battery
D^g_t	shut-down cost of generator g in time t
d^{ω}_t	demand in time t given scenario ω
$e_{m,h}$	hourly random noise in the intraday wind model for month m
$p^{\omega}_{k,t}$	dispatch decision from source k in time t given scenario ω
$p^{\omega}_{wind,t}$	wind power output in time t given scenario ω
$s_{m,d}$	day-to-day state vector in time (m, d)
s^{ω}_t	lost-demand in time t given scenario ω
u^g_t	unit commitment of generator g in time t
U^g_t	start-up cost of generator g in time t
$\hat{v}^n_m$	n-th iterated sampled observation for the value function approximation for month m
w_t	wind speed in time t
$w^{\text{day}}_{m,d}$	daily average wind value in time (m, d)
$\hat{w}^{\text{day}}_{m,d}$	exogenous information variable of daily average wind value realized in time (m, d)
x^w_{capa}	capacity acquisition of wind generator
x^b_{capa}	capacity acquisition of battery
$x_{m,d}$	vector of daily operational decisions in time (m, d)
$x_{1,m,d}$	vector of 1st stage decisions in the one-day operation model in time (m, d)
$x^{\omega}_{2,m,d}$	vector of 2nd stage decisions in the one-day operation model in time (m, d) given scenario ω

Functions

C	daily operational cost function
f	1st stage cost function in the one-day operation model
Q_{ω}	2nd stage cost function in the one-day operation model given scenario ω
$\bar{V}_m$	approximated value function for month m
$\hat{V}^{SR}_m$	surrogated function of the value function for month m
ϕ^{VF}	basis function for the value function approximation
ϕ^{WIND}	basis function for the wind model

One of the most promising new grid paradigms is the *microgrid* (MG) [3], which is for providing energy in a small and localized area with its own distribution grid. A MG has generally multiple distributed generators including renewable energy sources along with conventional fuel-based generators, and energy storage devices to make up for the intermittent nature of the renewable energy sources. The choice of a suitable generation mix is entirely site-specific depending on the availability of the various renewable