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A decentralized robust model for coordinated operation of smart distribution network and electric vehicle aggregators

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ABSTRACT

Aggregators act as a mediator between electric vehicles (EVs) and distribution network operator (DNO), providing mutual advantages for both. To achieve these advantages, the optimal operation of distribution network and EV aggregators (EVAs) should be coordinated. This paper aims at establishing a decentralized robust model to minimize the total cost of the system by operating the smart distribution network (SDN) and EVAs in a coordinative manner. To tackle the enforced operating uncertainties associated with wind generation and wholesale market price, an adaptive robust optimization (RO) approach is utilized enabling DNO to adjust different conservation levels throughout the operating horizon. In order to preserve the independency of EVAs and reduce the computational burden, the RO based model is solved using a decentralized algorithm which is developed based on the alternating direction method of multipliers (ADMM). Accordingly, the operating problems of DNO and EVAs are coordinated and optimized, independently. The effectiveness of proposed model is demonstrated using a modified 33-bus smart distribution network with multiple EVAs.

1. Introduction

With the growing air pollution and the global consumption of fossil fuels, governments tend to improve the current transportation systems. In this regards, electric vehicles (EVs) have gained increasing attention and it is expected that they will be extensively used in future transportation systems [1]. For example, the electric power system research institute (EPRI) predicts that 62% of US vehicle fleet will comprise plug-in hybrid electric vehicles by 2050 [2]. However, such a high integration of EVs into the distribution networks (DNs) will have significant effects on the optimal operation of future DNs. Accordingly, numerous studies have been conducted on EVs and their upcoming challenges and opportunities for the distribution network operators (DNOs).

Research studies are mainly conducted on optimal charging/discharging control strategies and exploiting benefits of EVs using vehicle-to-grid (V2G) capability [3]. A valley-filling pricing scheme is presented in [4] that encourages EVs to shift their charging demands to off-peak hours. Authors of [5] develop an algorithm to solve the optimal decentralized coordinated dispatch problem of renewable generations and EVs based on multi-agent systems. In [6], a power smoothing method is proposed using demand response of EVs which are connected to the DN to mitigate undesirable fluctuations of wind turbines. In [7], the daily energy losses, voltage deviations, and load unbalances of a low voltage DN with high penetration of EVs are analyzed. Likewise, a solution method is proposed to monitor the charging of EVs and apply corrective actions. In [8], a multi-objective model is presented to minimize total operation and emission costs of smart distribution networks (SDNs) by optimal charging/ discharging scheduling of EVs. In this paper, V2G capability and patterns of EVs are considered to generate pareto-optimal solutions. In [9], a Volt-VAR optimization model considering reactive power injection of EVs is proposed to minimize system power loss cost and operating cost of switched capacitor banks. Authors of [10] evaluate the impact of EVs on the residential distribution grids and propose a coordination mechanism to manage charging of EVs during peak periods. It would be technically intractable for DNO to control charging/discharging strategy of each EV directly when there are a large number of them integrated into the DN. Moreover, direct connection between the DNO and each EV causes a massive burden for the communication network. To cope with the mentioned challenges, a new entity, EV aggregator (EVA), is introduced in SDNs [11].

EVAs are the stakeholders responsible for controlling the charging/ discharging process of EVs and act as a mediator between the EVs and the DNO [12]. The EVAs use bidirectional communications to exchange data with EVs which are under their control and DNO [13]. In [14], a multi-objective optimization model for optimal operation of EVAs

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Nomenclature

Indices and Sets

t Index of time period from 1 to N_T.
i Index of EV aggregator from 1 to N_{EVA}.
e Index of electrical vehicles from 1 to N_{EV}.
j Index of DG from 1 to N_{DG}.
w Index of wind turbine from 1 to N_w.
n, m Index of distribution network buses.
k Index of ADMM iteration.
$\mathrm{EVA}_{(n)}$ Set of EV aggregators belonging to bus n.
$\mathrm{DG}_{(n)}$ Set of DGs belonging to bus n.
$\mathrm{WT}_{(n)}$ Set of wind turbines belonging to bus n.
$\mathrm{EV}_{(i)}$ Set of EVs controlling by aggregator i.
F Set of distribution network feeders.

Parameters

$a_{(j)}$, $b_{(j)}$, $c_{(j)}$ Cost function coefficients of DGj [\$/(MW)^2, \$/(MW), \$].
η^{chg}/η^{dis} Charging/discharging efficiency of EVs' battery.
$\pi^{WS}_{(t)}$ Forecasted price of wholesale market at time t [\$/MWh].
$P^{W}_{(w,t)}$ Forecasted power generation of wind turbine w at time t [MW].
μ_{arr}/σ_{arr} Mean/standard deviation related to arrival time of EVs [h].
μ_{dep}/σ_{dep} Mean/standard deviation related to departure time of EVs [h].
μ_{di}/σ_{di} Mean/standard deviation related to travelling distance of EVs [km].
$v_{(t)}$ Wind speed at time t [m/s].
$v_r/v_{ci}/v_{co}$ Rated/cut-in/cut-out speed of wind turbine [m/s].
$P_{r(w)}$ Rated power of wind turbine w [MW].
$\Gamma_{(\bullet)}$ Uncertainty budget related to uncertain variable $(\bullet)$.
$\xi_{(\bullet)}$ Degree of uncertainty related to uncertain variable $(\bullet)$.
C_{BI} Investment cost of EVs' battery [\$].
d_{DoD} Maximum depth of discharge of EVs' battery.
L_c EVs' battery cycle life.
di^{max} Maximum daily travel distance of EVs [km].
$SDC_{(j)}$ Shut-down cost of DGj [\$].
$SUC_{(j)}$ Start-up cost of DG j [\$].
$UR_{(j)}/DR_{(j)}$ Ramp up/down of DG j [MW/h].
$UT_{(j)}/DT_{(j)}$ Minimum up/down time of DG j [h].
$b_{(n,m)}/g_{(n,m)}$ Susceptance/conductance of feeder between buses n–m [1/Ω].
V_{nom} Nominal voltage of distribution network [kV].
$\pi^{BD}_{(e)}$ Degradation cost of EVs' battery [\$/kWh].
SOC^{ini} Initial state of charge of EVs' battery [kWh].
$P^{L}_{(n,t)}$ Load demand in bus n at time t [MW].
ε Allowable voltage deviation.
ε_{thr} Threshold of convergence criteria in ADMM method.
ρ Penalty factor in ADMM method.
di Daily travel distance of EVs [km].
t_{arr}/t_{dep} Arrival/departure time of EVs [h].
$Econs^{EV}_{(e)}$ Total energy consumption of EV e at next day [kWh].

Variables

$u_{(j,t)}$ Binary variable indicating commitment of DG j at time t.
$u^{ON}_{(j,t)}/u^{OFF}_{(j,t)}$ Binary variable indicating start-up/shut down status of DG j at time t.
$P^{DG}_{(j,t)}$ Power generation of DGj at time t [MW].
$u^{chg}_{(e,t)}/u^{dis}_{(e,t)}$ Binary variable indicating charge/discharge status of EVs' battery e at time t.
$P^{Agg}_{(i,t)}$ Amount of exchanged power with distribution network which is determined by the aggregator i at time t [MW].
$P^{WS}_{(t)}$ Purchased power from the wholesale market at time t [MW].
$P^{EVchg}_{(e,t)}/P^{EVdis}_{(e,t)}$ Charged/discharged power of EV e at time t [kW].
$SOC^{EV}_{(e,t)}$ State of charge of EV e at time t [kWh].
υ, η, yp, yw Auxiliary variables in robust optimization approach.
$P^{flow}_{(m,n,t)}$ Power flow between buses n–m at time t [MW].
$\Delta V_{(n,t)}$ Voltage deviation of bus$n$ at time t [kV].
$\theta_{(n,m,t)}$ Voltage angle difference between buses n–m at time t [rad].
$\lambda_{(i,t)}$ Lagrangian multiplier related to aggregator i at time t in ADMM method [\$/MW].
$P^{DNO}_{(i,t)}$ Amount of exchanged power between distribution network and aggregator i at time$t$ which is determined by DNO [MW].

Function

F^{arr}/F^{dep} Probability distribution function related to arrival/departure time of EVs.
F^{di} Probability distribution function related to travel distance of EVs.
L_ρ Augmented Lagrangian function.

Symbol

$\overline{(\bullet)}/\underline{(\bullet)}$ Maximum/minimum bounds of variable $(\bullet)$.
$\widetilde{(\bullet)}$ Value of uncertain variable $(\bullet)$.
$\widehat{(\bullet)}$ Maximum deviation of variable $(\bullet)$ from its forecasted.

Acronyms

ADMM Alternating Direction Method of Multipliers.
DN Distribution Network.
DNO Distribution Network Operator.
EV Electric Vehicle.
EVA Electric Vehicle Aggregator.
RO Robust Optimization.
SDN Smart Distribution Network.
V2G Vehicle to Grid.

which are integreted in a microgrid is proposed to minimize total loss, voltage deviation, and security margin related to the line current. Authors of [15] analyze the bidding strategy problem of an EVA that participates in the day-ahead energy market. The problem is formulated using a stochastic robust optimization model in which uncertainties in the day-ahead market prices and in the driving requirements of EVs are modeled using scenarios and confidence bounds, respectively. Ref. [16] proposes a bidding strategy for an EVA to maximize its profits in the energy and reserves markets, while compensating battery degradation of EV owners. Authors of [17] formulate a bi-objective charging scheduling problem that aims to maximize total profit of multiple EVAs considering the collaboration among them. In [18], an aggregated optimal charging strategy is proposed to minimize total charging cost of EVAs considering V2G service of EVs. In [19], an optimal day-ahead operation planning model for microgrids with EVs is described. The day-ahead operation plan aims to minimize microgrid operation daily costs in the presence of an EVA while considering the possible economic relationships between the EVA and operator of microgrid. In [12] a pricing mechanism is proposed to coordinate EVAs in a DN. The objective is to minimize total operation cost of system while alleviating congestion of feeders. In [20] a coordination mechanism is proposed for self-interested EVAs which incentivizes EVAs to report their energy