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Incorporating price-responsive customers in day-ahead scheduling of smart distribution networks

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ABSTRACT

Demand response and real-time pricing of electricity are key factors in a smart grid as they can increase economic efficiency and technical performances of power grids. This paper focuses on incorporating price-responsive customers in day-ahead scheduling of smart distribution networks under a dynamic pricing environment. A novel method is proposed and formulated as a tractable mixed integer linear programming optimization problem whose objective is to find hourly sale prices offered to customers, transactions (purchase/sale) with the wholesale market, commitment of distribution generation units, dispatch of battery energy storage systems and planning of interruptible loads in a way that the profit of the distribution network operator is maximized while customers' benefit is guaranteed. To hedge distribution network operator against financial risk arising from uncertainty of wholesale market prices, a risk management model based on a bi-level information-gap decision theory is proposed. The proposed bi-level problem is solved by recasting it into its equivalent single-level robust optimization problem using Karush–Kuhn–Tucker optimality conditions. Performance of the proposed model is verified by applying it to a modified version of the IEEE 33-bus distribution test network. Numerical results demonstrate the effectiveness and efficiency of the proposed method.

1. Introduction

Nowadays, power systems are developing toward smart grids specifically at the distribution level, aiming at providing financial and technical benefits for both system operators and customers [1]. With the development of smart grids at the distribution level, Distributed Energy Resources (DERs) such as renewable and non-renewable Distributed Generation (DG) units, Battery Energy Storage Systems (BEESs) and Demand Response (DR) programs are being integrated into the distribution network operation [2]. The presence of one or more of these equipments along with the uncertainties will create more complex and challenging tasks in day-ahead scheduling of smart distribution networks.

As the key feature of smart distribution networks, optimal scheduling have attracted great attention, which can be categorized into supplied side and demand side point of views. References [3–6] focus on the supplied side issues. A two-stage hierarchical framework for day-ahead scheduling of distribution network is proposed in [3]. The first stage of the proposed framework deals with electrical power purchasing from the wholesale market and commitment of DGs, whereas the decisions related to the dispatching of committed DGs, participating in real-time market and planning of curtailable loads are made in the second stage. The authors of [4] propose an optimal power flow algorithm to develop a generalized formulation aiming at minimizing the total operation cost of smart distribution network considering network constraints. In [5], a multi-objective approach for day-ahead scheduling of distribution network is proposed based on stochastic optimization. The paper aims at minimizing the emission and operating costs. In [6], a unified operation model is proposed in which the network topology and hourly scheduling of DGs as well as curtailable loads are determined in a way that total operation cost of distribution network is minimized. On the other hand, thanks to advancements in smart grid technologies, the demand side issues are also received growing attention. Authors of [7] propose a model for smart energy management of a residential customer in which electrical and thermal appliances are jointly scheduled to minimize electricity cost. In [8], customers' opportunity to adjust their consumption patterns in response to real-time pricing, with the goal of decreasing their electricity bills, has been investigated. In [9], a day-ahead pricing model is proposed to maximize profit of energy providers where in consumers satisfaction is

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Nomenclature

Indices
- t, t' indices of optimization period
- j index of non-renewable DG units
- c index of customer types
- w index of wind turbines
- e index of battery energy storage systems
- d index of interruptible loads
- k index of steps of bid-quantity offers
- i, n, m indices of distribution network buses
- f index of distribution network feeders

Parameters
- $\widetilde{\lambda_{(t)}^{WS}}$ forecasted day-ahead wholesale market price at hour t
- $UR_{(j)}, DR_{(j)}$ ramp up/down of DG unit j
- $UT_{(j)}, DT_{(j)}$ minimum up/down time of DG unit j
- $\underline{P_{(j)}^{DG}}, \overline{P_{(j)}^{DG}}$ minimum/maximum power limit of DG unit j
- $SUC_{(j)}, SDC_{(j)}$ start-up/shut down cost of DG unit j
- $a_{(j)}, b_{(j)}, c_{(j)}$ cost function coefficients of DG unit j
- $P_{(t,i,c)}^{L0}$ initial active demand of customer type c in bus i at hour t
- $\varepsilon_{(t,c)}, \varepsilon'_{(t,t',c)}$ self-elasticity of customer type c indicating its variation during hour t to the price during that hour/ cross-elasticity of customer type c indicating its variation during hour t to hour t'
- $\overline{\rho_{(t,c)}}$ maximum sale price offered to customer type c at hour t
- $\rho 0_{(c)}$ based electricity price of customer type c
- $E_{(i,c)}^{L}$ energy requirement of customer type c in bus i
- $\underline{\Delta_{(d)}}, \overline{\Delta_{(d)}}$ minimum/maximum possible interruption level for load d
- $\Delta_{(d,k)}$ interruption level for load d in step k
- $\pi_{(d,k)}$ offered price of interruptible load d in step k
- $r_{(m,n)}, x_{(m,n)}$ resistance/reactance between bus m and n
- $\overline{I_{Sub}}$ maximum current flow allowed at substation
- $\overline{I_{(m,n)}}$ maximum current flow allowed between bus n and m
- $\underline{V_{(n)}}, \overline{V_{(n)}}$ minimum/maximum voltage limit in bus n
- $p_{(n)}^{L}, q_{(n)}^{L}$ active/reactive power of load consumption in bus n
- $\vartheta_{(t)}$ wind speed at hour t
- η^{c}, η^{d} battery charging/discharging efficiency coefficients
- $\underline{SOC_{(e)}}, \overline{SOC_{(e)}}$ minimum/maximum capacity of battery energy storage system e
- $\underline{P_{(e)}^{Bc}}, \overline{P_{(e)}^{Bd}}$ minimum/maximum amount of power dispatch of energy storage system e
- $\sigma_{(t)}^{L}, \sigma_{(t)}^{w}$ load/wind percentage forecasted error at hour t
- $\underline{P_{(t,i,c)}^{L}}, \overline{P_{(t,i,c)}^{L}}$ minimum/maximum demand limits for customer type c in bus i at hour t
- γ payment coefficient
- $Profit^{exp}$ expected profit which calculated based on $\widetilde{\lambda_{(t)}^{WS}}$ in IGDT method
- α profit deviation factor in IGDT method

Function and variables
- $\lambda_{(t)}^{WS}$ day-ahead wholesale market price at hour t
- $\rho_{(t,c)}$ sale price offered to customer type c at hour t
- $P_{(t,j)}^{DG}, Q_{(t,j)}^{DG}$ day-ahead scheduled active/reactive power of DG unit j at hour t
- $P_{(t,w)}^{W}, Q_{(t,w)}^{W}$ day-ahead scheduled active/reactive power of wind turbine w at hour t
- $P_{(t,i,c)}^{L}, Q_{(t,i,c)}^{L}$ forecasted active/reactive demand of customer type c in bus i at hour t
- $P_{(t,d)}^{IL}, Q_{(t,d)}^{IL}$ day-ahead scheduled active/reactive power interruption for interruptible load d at hour t
- $\delta_{(t,d,k)}$ amount of interruption for interruptible load d in step k at hour t
- $P_{(t,w)}^{W}$ power generation of wind turbine w at hour t
- $P_{(t,e)}^{Bd}, P_{(t,e)}^{Bc}$ scheduled discharge/charge power of energy storage systems e at hour t
- $bs_{(t,e)}^{d}, bs_{(t,e)}^{c}$ binary variables indicating discharging/charging status of battery energy storage system e at hour t
- $SOC_{(t,e)}$ capacity of battery energy storage system e at hour t
- $u_{(t,j)}, y_{(t,j)}, z_{(t,j)}$ binary variables for DG unit commitment/start-up/shut down status of DG unit j at hour t
- $u_{(t,j)}^{ON}, u_{(t,j)}^{OFF}$ binary variables indicating the start-up/shut-down times of DG unit j at hour t
- $P_{(m,n)}^{flow}, Q_{(m,n)}^{flow}$ active/reactive power flow of feeder between bus n and m
- $V_{(n)}$ voltage magnitude in bus n
- $I_{(m,n)}$ current magnitude flow between bus n and m
- $l_{(m,n)}, \upsilon_{(n)}$ auxiliary variables introduced in the AC power flow equations
- ξ confidence interval in IGDT method
- $\hat{\xi}$ robustness function in IGDT method
- $Profit$ objective function in IGDT method
- $\mu_{(t)}^{1}, \mu_{(t)}^{2}$ lagrangian multipliers

Sets
- RR set of robust region for wholesale market price in IGDT method
- DV set of decision variables for day-ahead scheduling in the smart distribution network

considered. A decentralized optimization approach is developed in [10] to minimize total cost of utility company in a way that the most smooth demand profile is yielded.

In reality, day-ahead scheduling of smart distribution network is exposed to the uncertainties of electricity price (on the supply side) and load (on the demand side). Ignoring the risk of mentioned uncertainties may impose great financial losses to the Distribution Network Operator (DNO). In this regard, the stochastic optimization methods together with risk measures are often used to tackle financial risk arising from the uncertainties in which Probability Density Functions (PDFs) are utilized to represent uncertain parameters [11]. A hierarchical stochastic method is presented in [12] to minimize expected procurement cost of a distribution company subjected to a risk constrain. A coordinated model of curtailable loads and DGs is proposed in [13] based on a multi-stage stochastic optimization to minimize expected operation costs of microgrids and handle imposed risk using scheduled reserves. In [14], operation optimization of microgrids is established with the goal of profit maximization and risk management. The accuracy and optimality of the stochastic methods rely on the accuracy of the PDF and number of scenarios which are considered within the optimization problem. The absence of sufficient historical data leads to inaccurate fitted PDF and consequently wrong results. In addition, with increasing the number of scenarios, the computational complexity