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Robust day-ahead scheduling of smart distribution networks considering demand response programs

Mohammadreza Mazidi[a], Hassan Monsef[a,*], Pierluigi Siano[b]

[a] School of Electrical and Computer Engineering, University of Tehran, Iran
[b] Department of Industrial Engineering, University of Salerno, Fisciano, Italy

HIGHLIGHTS

- Proposing a tractable adaptive min–max–min robust formulation.
- Introducing a decomposition algorithm based on dual cutting planes.
- Presenting a full model of DR program for both energy and reserve scheduling.
- Conducting a Monte Carlo simulation analysis to justify accuracy and robustness.

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ABSTRACT

Increasing penetration of variable loads and renewable resources in smart distribution networks brings about great challenges to the conventional scheduling and operation due to the uncertain nature. This paper presents a novel uncertainty handling framework, based on the underlying idea of robust optimization approach, to portray the uncertainties of load demands and wind power productions over uncertainty sets. Accordingly, a tractable min–max–min cost model is proposed to find a robust optimal day-ahead scheduling of smart distribution network immunizing against the worst-case realization of uncertain variables. In addition, considering demand response programs as one of the important resources in the smart distribution network, participation of customers in both energy and reserve scheduling is explicitly formulated. As the proposed min–max–min cost model cannot be solved directly by commercial optimization packages, a decomposition algorithm is presented based on dual cutting planes to decouple the problem into a master problem and a sub-problem. The master problem finds the day-ahead scheduling, while the sub-problem determines the worst-case realization of uncertain variables within uncertainty sets. Computational results for the modified version of IEEE 33-bus distribution test network demonstrate the effectiveness and efficiency of the proposed model.

1. Introduction

Nowadays, power systems are developing toward smart grids to provide financial and technical benefits for both system operators and customers. With development of smart grids at 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 [1,2]. 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 the smart distribution networks (SDNs).

From an optimization perspective, day-ahead scheduling of the SDNs is a high computational optimization problem which can be solved using deterministic or stochastic approaches. Refs. [3–5] focus on deterministic approaches. A two-stage hierarchical framework for day-ahead scheduling of distribution networks is proposed in [3]. The first stage of the proposed framework deals with operational decisions on purchases from the day-ahead 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 study in [4] uses an optimal power flow algorithm to develop a generalized formulation for minimizing the total operation cost of the SDN considering network constraints. In [5], a fuzzy-logic-based

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* Corresponding author.

E-mail addresses: mrezamazidi@ut.ac.ir (M. Mazidi), hmonsef@ut.ac.ir (H. Monsef), psiano@unisa.it (P. Siano).

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Nomenclature

Indices

b	index of battery energy storage systems, $b = 1, 2, \ldots, N_{BESS}$
d	index of demand response providers, $d = 1, 2, \ldots, N_{\mathrm{DRP}}$
i	index of industrial loads, $i = 1, 2, \ldots, N_{\mathrm{IL}}$
j	index of non-renewable DG units, $j = 1, 2, \ldots, N_{\mathrm{DG}}$
k	index of steps of bid-quantity offers, $k = 1, 2, \ldots, K$
n, m	index of distribution network buses, $n = 1, 2, \ldots, N_{\mathrm{Bus}}$
t	index of optimization periods, $t = 1, 2, \ldots, N_{\mathrm{T}}$
w	index of wind turbines, $w = 1, 2, \ldots, N_{\mathrm{W}}$
ϑ	index of iterations of decomposition algorithm
ξ	index of binary variables used for discretization

Parameters

ρ_g^{DA}	day-ahead wholesale market price
$a,\ b,\ c$	cost function coefficients of DG units
SUC	start-up cost of DG units
$UR,\ DR$	ramp up/down of DG units
$UT,\ DT$	minimum up/down time of DG units
$\underline{P_{DG}},\ \overline{P_{DG}}$	minimum/maximum power limit of DG units
CI	power imbalance cost
$r,\ x$	resistance/reactance of feeders
$\overline{I_{Sub}}$	maximum current flow allowed at substation
$\underline{V}, \overline{V}$	minimum/maximum limit of bus voltage
$\underline{p_L}, q_L$	active/reactive power of loads
$\overline{P_{IL}}$	maximum load reduction offered by industrial loads
$\overline{P_{DRP}}$	maximum load reduction offered by DRPs
$O_{min}^d,\ O_{max}^d$	minimum/maximum load reduction offered by DRPs
O	load reduction offered by DRPs
$\eta^c,\ \eta^d$	battery charge/discharge efficiency coefficients
$\underline{SOC},\ \overline{SOC}$	minimum/maximum capacity of BESSs
$\underline{P_L},\ \overline{P_L}$	lower/upper bound of uncertain load
$\underline{P_W}, \overline{P_W}$	lower/upper bound of uncertain wind power
$\underline{\Gamma_L},\ \overline{\Gamma_L}$	lower/upper bound of loads uncertainty budgets
$\underline{\Gamma_W},\ \overline{\Gamma_W}$	lower/upper bound of wind power uncertainty budgets
$\sigma_\bullet$	standard deviation of ($\bullet$) uncertain variable (e.g., σ_L)
$\Gamma_\bullet$	uncertainty budget of ($\bullet$) uncertain variable (e.g., $\underline{\Gamma_L}$ and $\overline{\Gamma_L}$)
$\beta_\bullet$	forecast error of ($\bullet$) uncertain variable (e.g., β_L)

Functions and variables

$P_{grid}^{DA},\ Q_{grid}^{DA}$	day-ahead scheduled active/reactive power of substation
$P_{DG}^{DA},\ Q_{DG}^{DA}$	day-ahead scheduled active/reactive power of DG units
$P_W^{DA},\ Q_W^{DA}$	day-ahead scheduled active/reactive power of wind turbines
$P_L^{DA},\ Q_L^{DA}$	day-ahead forecasted active/reactive load in each bus
$P_{IL}^{DA},\ Q_{IL}^{DA}$	day-ahead scheduled active/reactive load reduction of industrial loads
$P_{DRP}^{DA},\ Q_{DRP}^{DA}$	day-ahead scheduled active/reactive load reduction of demand response providers
P_{DG}^{RT}	real-time active power dispatch of DG units
P_{IL}^{RT}	real-time active load reduction of industrial loads
P_{DRP}^{RT}	real-time active load reduction of demand response providers
R_{DG}^{DA}	day-ahead scheduled reserve capacity of DG units
R_{IL}^{DA}	day-ahead scheduled reserve capacity of industrial loads
R_{DRP}^{DA}	day-ahead scheduled reserve capacity of demand response providers
P_W^u	uncertain wind power
P_L^u	uncertain load
CE_{DG}	cost function for power production of DG units
CR_{DG}	cost function for provided reserve capacity of DG units
CE_{IL}	cost function for load reduction of industrial loads
CR_{IL}	cost function for provided reserve capacity of industrial loads
CE_{DRP}	cost function for load reduction of demand response providers
CR_{DRP}	cost function for provided reserve capacity of demand response providers
CS_{DG}	cost function for start-up of DG units
Imb	imbalance power in real-time operation
o	amount of accepted load reduction of DRPs in each step
π	offered price of DRPs in each step
$P_{Bd}^{DA},\ P_{Bc}^{DA}$	scheduled battery discharge/charge power
SOC	capacity of battery energy storage systems
u, y, z	binary variables for DG unit commitment/start-up/shut down status
$P^f,\ Q^f$	active/reactive power flow of feeders
$l,\ v$	auxiliary variables introduced in the AC power flow equations
$LB,\ UB$	lower/upper bound of decomposition algorithm

Sets

U_L	uncertainty set for load
U_W	uncertainty set for wind power
Ξ^{DA}	feasible set for day-ahead of smart distribution network
Ξ^{RT}	feasible set for real-time operation of smart distribution network
Ξ^{MP}	feasible set for the master problem
Ξ^{SP}	feasible set for the sub-problem

approach is proposed to schedule distribution network with the objective of minimizing operation and emission costs. However, due to the lack of accurate forecasting methods [6], deterministic approaches are not acceptable for day-ahead scheduling of the SDN. In stochastic approaches, uncertain variables are modeled by means of probability density functions (PDFs). In [7], a model is developed to minimize the expected operation cost of distribution companies while the risk imposed by uncertainties is restricted to a predetermined level. The proposed stochastic model only focuses on the energy scheduling without considering renewable energy units and demand response. The authors of [8] propose a probabilistic model for estimating spinning reserve in micro-grids. In the proposed model, the uncertainties of wind and solar power and load along with unreliability of DG units are considered. A two-stage stochastic energy and reserve management approach for micro-grids is proposed in [9]. In the first-stage, the optimal energy scheduling is determined based on the load, wind and solar forecasts. The optimal spinning reserve is estimated using sensitivity analysis in the second-stage. In [10], a risk based two-stage stochastic optimization model is proposed for day-ahead scheduling of the SDN with objective of operation cost minimization and risk management.

Thanks to recent advancements in smart grid technologies, DR can be employed as a main resource in economic and reliable operation of the SDNs. Basically DR is defined as consumers' ability to modify their normal consumption in response to variable electricity prices or incentive payments [11]. The study in [12] has incorporated load curtailment and load shifting DR programs in energy scheduling of the industrial virtual power plants to maximize profit. In [13], a probabilistic methodology aiming at integrating DR in the distribution energy market based on distribution locational marginal price is introduced. Besides energy scheduling,