Electrical Power and Energy Systems 72 (2015) 91–98

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Energy and reserve scheduling under correlated nodal demand uncertainty: An adjustable robust optimization approach

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ARTICLE INFO

Article history:
Received 1 February 2015
Accepted 16 February 2015
Available online 17 March 2015

Keywords:
Adjustable robust optimization
Benders decomposition
Binary expansion
Correlated nodal demand uncertainty
Generation scheduling

ABSTRACT

This paper presents a nonparametric approach based on adjustable robust optimization to consider correlated nodal demand uncertainty in a joint energy and reserve scheduling model with security constraints. In this model, up- and down-spinning reserves provided by generators are endogenously defined as a result of the optimization problem. Adjustable robust optimization is used to characterize the worst-case load variation under a given user-defined uncertainty set. This paper differs from recent previous work in two respects: (i) nonparametric correlations between nodal demands are accounted for in the uncertainty set and (ii) based on the binary expansion linearization approach, a mixed-integer linear model is provided for the optimization related to the worst-case demand. The resulting problem is formulated as a trilevel program and solved by means of Benders decomposition. Empirical results suggest that the effect of nodal correlations can be effectively captured by the robust scheduling model.

Introduction

The determination of appropriate levels of resources constitutes a crucial issue in power system operation with significant impact on energy prices and power system security [1,2]. Spinning reserves are part of the ancillary services that provide the system operator with necessary leeway to face load variability while withstanding the most relevant contingencies [3]. The joint schedule of energy and reserves is one way to capture the interactions between both commodities [2–4].

The majority of power systems all over the world are operated under the traditional $n-1$ and $n-2$ deterministic criteria [5]. Within such context, the optimal levels of reserves are provided by deterministic contingency-constrained models that explicitly consider the operation associated with each credible contingency state. Relevant applications of such models to co-optimize energy and reserves can be found in [3,4,6,7].

Stochastic models [8] are also employed in the scheduling of generators. The characterization of uncertainty through scenarios and their probabilities allows accounting for probabilistic structures present in the underlying uncertainty process, e.g., correlations between nodal demands and renewable injections. Stochastic models aim to determine the optimal levels of resources, e.g., energy and reserves, by properly using the available information about the uncertainty structure while guaranteeing system security in a probabilistic fashion.

Considerable attention has been recently paid to robust optimization in generation scheduling [6,7,9–11]. As a distinctive feature, uncertainty is characterized endogenously, thereby avoiding the need for explicitly modeling the system operation under each contingency or scenario. To that end, robust counterparts are formulated as multi-level optimization programs. Robust models find a solution that is feasible for all possible realizations of the uncertainty in a given polyhedral uncertainty set [12]. The polyhedral uncertainty set allows controlling the conservativeness level of the model by means of a user-defined parameter. Such parameter constrains the number of uncertainty coefficients that can deviate from their nominal value.

Recent works [9,10] propose two-stage or adjustable robust optimization (ARO) [13,14] to deal with nodal injection uncertainty in unit commitment. In both works, a multi-level robust counterpart is formulated and Benders decomposition is applied.

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[1] CNPq Scholarship Student – Brazil.
[2] The work of J.M. Arroyo was supported by the Ministry of Science of Spain, under CICYT Project ENE2012-30679; the European Commission, under Grant Agreement Number 309048; and the Junta de Comunidades de Castilla-La Mancha, under project POII-2014-012-P.

http://dx.doi.org/10.1016/j.ijepes.2015.02.015
0142-0615/

Nomenclature

Sets

C	set of contingency indexes
I	set of generator indexes
I_b	set of indexes of generators connected to bus b
$\mathcal{L}$	set of transmission line indexes
N	set of bus indexes
Q	set of polyhedral constraints bounding the demand

Functions

$c_i^P(\cdot)$	energy cost function offered by generator i

Constants

Γ	conservativeness parameter
ρ	correlation parameter
$\mathbf{\Sigma}$	estimated nodal demand covariance matrix
$\Sigma_{b,b'}$	element (b, b') of $\mathbf{\Sigma}$
A_i^k	availability parameter that is equal to 0 if generator i is unavailable under contingency state k, being 1 otherwise
A_l^k	availability parameter that is equal to 0 if line l is unavailable under contingency state k, being 1 otherwise
C_i^D	cost rate offered by generator i to provide down-spinning reserve
C_i^f, C_i^v	coefficients of the energy cost function offered by generator i
C^I	power-imbalance cost coefficient
C_i^U	cost rate offered by generator i to provide up-spinning reserve
$\hat{D}_b$	nominal demand at bus b
$\overline{D}_b$	maximum demand level at bus b
$\underline{D}_b$	minimum demand level at bus b
$\overline{F}_l$	power flow capacity of line l
$fr(l)$	sending or origin bus of line l
h_q	bound of the q-th general polyhedral constraint
H_b	number of discrete levels of D_b
J_b	number of binary variables used in the discretization of D_b
$\mathbf{L}$	lower triangular matrix that satisfies the equality $\mathbf{\Sigma} = \mathbf{L}\mathbf{L}^T$
$L_{b,b'}$	element (b, b') of $\mathbf{L}$
M	big number used in the disjunctive constraints
n	number of system components
$\overline{P}_i$	capacity of generator i
$\underline{P}_i$	minimum power output of generator i
$\overline{R}_i^D$	upper bound for the down-spinning reserve contribution of generator i
$\overline{R}_i^U$	upper bound for the up-spinning reserve contribution of generator i
s_b	discretization step for D_b
$to(l)$	receiving or destination bus of line l
$W_{b,q}$	element (b, q) of the matrix representing a general polyhedral constraint bounding the demand
x_l	reactance of line l
z	scaling factor

Decision variables

α	approximation of the system power imbalance in the Benders master problem
δ^{wc}	auxiliary variable representing the worst-case system power imbalance
Δ^{wc}	system power imbalance under the worst-case contingency
δD_b	auxiliary variable used in the linearization of the absolute value of the power imbalance at bus b under the worst-case contingency
ΔD_b^k	auxiliary variable used in the linearization of the absolute value of the power imbalance at bus b under contingency k
δP_b	auxiliary variable used in the linearization of the absolute value of the power imbalance at bus b under the worst-case contingency
ΔP_b^k	auxiliary variable used in the linearization of the absolute value of the power imbalance at bus b under contingency k
θ_b	phase angle at bus b in the pre-contingency state
θ_b^k	phase angle at bus b under contingency k
μ_b^k	variable equal to the product $\beta_b^k D_b$
ξ_{jb}^k	variable equal to the product $\beta_b^k u_{jb}$
D_b	demand at bus b
$e_b^{(+)}$	positive error on the demand at bus b
$e_b^{(-)}$	negative error on the demand at bus b
f_l	power flow of line l in the pre-contingency state
f_l^k	power flow of line l under contingency k
p_i	power output of generator i in the pre-contingency state
p_i^k	power output of generator i under contingency k
r_i^D	down-spinning reserve provided by generator i
r_i^U	up-spinning reserve provided by generator i
u_{jb}	binary variable used in the discretization of D_b
v_i	binary variable that is equal to 1 if generator i is scheduled in the pre-contingency state, being 0 otherwise

Dual variables

β_b^k	dual variable associated with the power balance equation at bus b under contingency k
γ_i^k	dual variable associated with the constraint imposing the lower bound for p_i^k
π_l^k	dual variable associated with the constraint imposing the lower bound for f_l^k
σ_l^k	dual variable associated with the constraint imposing the upper bound for f_l^k
χ_i^k	dual variable associated with the constraint imposing the upper bound for p_i^k
$\psi_b^{(D)k}$	dual variable associated with the constraint imposing the lower bound for δD_b under contingency k
$\psi_b^{(P)k}$	dual variable associated with the constraint imposing the lower bound for δP_b under contingency k
ω_l^k	dual variable associated with the equation relating power flow and phase angles for line l under contingency k

However, the presence of bilinear and highly nonconvex terms prevents Benders decomposition from guaranteeing the attainment of global optimality. Thus, such approaches rely on Monte Carlo sampling [9] or an iterative heuristic [10] in order to assess the quality of the suboptimal solutions achieved. Aside from their difficulties in proving optimality, the ARO-based approaches [9,10] feature an additional shortcoming with respect to traditional stochastic approaches for unit commitment under demand uncertainty [8],