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A data driven multi-state model for distribution system flexible planning utilizing hierarchical parallel computing

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HIGHLIGHTS

- Time-varying variables are modeled in terms of amplitude and profile.
- Probabilistic adaption of initial plans to multiple states is considered.
- The MINLP-based DSEP is solved by an integrated CE and DE algorithm.
- A three-hierarchy parallel platform reduces CPU time of DSEP.
- Flexibility of DSEP is enhanced and extra adaption costs are reduced.

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ABSTRACT

With the development of smart grid and electricity market, the uncertainty for power flow is greatly aggravated, and thus leads to a great challenge on the traditional expansion methods for distribution systems to satisfy the future demands. In this paper, a data-driven multi-state distribution system expansion planning (DSEP) model is explored. Innovatively, amplitude values and profiles of uncertain factors in distribution systems are considered separately. Based on the massive historical measurement data, kernel density estimation and adaptive clustering are utilized to aggregate the typical amplitudes and profiles of time-varying variables respectively without prior knowledge. Consolidating all the uncertain factors, a multi-state model is established which extends DSEP into the deterministic initial planning and the probabilistic re-planning. The minimization of the overall planning cost is considered as the objective, which takes the initial planning costs and the expected costs of the initial plans being adapted to other future states into account. In this way, the flexibility of DSEP can be greatly enhanced and extra investments caused by frequent adjustments of plans are reduced. To avoid the rapid growth of CPU time due to multi-state model utilization, an integrated differential evolution and cross entropy algorithm implemented on a three-hierarchy parallel platform is proposed. The feasibilities of the proposed data-driven multi-state DSEP model and the parallel integrated solution method are demonstrated by numerical studies on a realistic 61-bus distribution system.

1. Introduction

1.1. Background and literature review

The distribution system expansion planning (DSEP) is a classic problem in power systems. Conventional DSEP studies care about the optimal expansions of distribution network assets to satisfy the forecasted load with the technical and economic constraints be respected [1]. The expansions include replacement and addition of feeders, reinforcement of existing substations, construction of new substations, and installation of new transformers. There are two types of DSEP models: static and multistage [2]. In the static DSEP, objective is aimed at accommodating the demand projected at the end of the planning period. The multistage DSEP defines not only the ideal investments, but also the most appropriate time to implement such investments. Due to the coupling between stages, it is much more difficult to formulate and solve the multistage DSEP [3].

DSEP is highly complex and NP-hard, due to the binary decision

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Nomenclature

Acronyms

DSEP	distribution system expansion planning
DR	demand response
DG	distributed generation
ES	energy storage
EV	electric vehicles
IES	integrated energy system
GA	genetic algorithm
DE	differential evolution
CE	cross entropy
PDF	probabilistic density function
WTG	wind turbine generator
PV	photovoltaic
TOU	time of use
RTP	real time pricing
CNY	chinese yuan
UA	uncertainty analysis
DED	day-ahead economical dispatching
AMI	advanced metering infrastructure
GIS	geographic information system
MIS	meteorological information system
SMP	shared-memory processor
MPI	message passing interface
LSE	load service entity
CHP	combined heat and power production
CHCP	combined heat, cooling, and power production
KDE	kernel density estimation
PAA	piecewise aggregate approximation
DB	davies-bouldin
ISE	integral square error
MINLP	mixed-integer nonlinear programming

Sets

Ω^{L}, Ω^{A}	set of candidate feeders and set of available feeder types respectively
Ω^{SR}, Ω^{SO}	sets of existing substations with and without reinforcement options respectively
Ω^{SC}	set of candidate substations
Ω^{S}	set of substations, defined as $\Omega^{S} = \Omega^{SR} \cup \Omega^{SO} \cup \Omega^{SC}$
Ω^{R}, Ω^{C}	sets of available capacity types for substation reinforcement and construction respectively.
Ω^{N}	set of nodes in the distribution system of interest
T	set of time intervals
Ω^{i}_{plot}	set of land plots fed by node i

Variables and parameters

$x^{L}_{ij,a}$	binary decision variable for feeder i-j with type a
$y^{SR}_{i,b}$	binary decision variable for substation reinforcement at node i with type b
$y^{SC}_{i,c}$	binary decision variable for substation construction at node i with type c
π^{L}, π^{S}	capital recovery factors for feeders and substations respectively
a, b, c	Type code for feeder construction, substation reinforcement and substation construction respectively.
$c^{L}_{ij,a}$	construction cost of feeder i-j with type a (CNY/km)
$c^{SR}_{i,b}$	reinforcement cost of substation i with type b (CNY)
$c^{SC}_{i,c}$	construction cost of substation i with type c (CNY)
l_{ij}	length of feeder i-j (km)
c^{oper}_{i}	substation operation cost at node i (CNY/MVA)
δ	days in a year
c^{E}	network loss cost (CNY/MWh)
$g_{ij,a}$, $b_{ij,a}$	conductance and susceptance of feeder i-j with type a
G_{ij}, B_{ij}	real part and imaginary part of the nodal admittance matrix
n^{L}, n^{S}	feeder lifespan and substation lifespan
$\theta_{ij,t}$	the phase angle deviation of feeder i-j in time interval t
ε	interest rate
$P^{S}_{i,t}$, $Q^{S}_{i,t}$	active and reactive power injections at node i in time t (MW, Mvar)
$\bar{S}_{ij,a}$	apparent power capacity of feeder i-j with type a (MVA)
$\bar{S}^{0}_{i}$	apparent power capacity of the existing substation at node i (MVA)
$\bar{S}^{SR}_{i,b}$	added apparent power capacity of the existing substation with reinforcement type b at node i (MVA)
$\bar{S}^{SC}_{i,c}$	apparent power capacity of the candidate substation with type c at node i (MVA)
$\underline{U}_{i}$, $\bar{U}_{i}$	voltage limits of node i
n^{D}, n^{Sub}	numbers of nodes and substations in a distribution system
n^{T}	intervals number in a day
$P^{CH}_{i,t}$, $P^{ES}_{i,t}$	the equivalent demand and charging/discharging power of ES at node i in time t
$P^{DG}_{i,t}$, $Q^{DG}_{i,t}$	active and reactive powers of DG at node i in time t (MW, Mvar)
$P^{D}_{i,t}$, $Q^{D}_{i,t}$	active and reactive power demands at node i in time t (MW, Mvar)
κ_{t}	electricity price in time t (CNY)
u_{t}	ternary decision variable for battery states: $1 \rightarrow$ charging, $-1 \rightarrow$ discharging; $0 \rightarrow$ floating
α	weight coefficient
$S^{ES}_{i,t}$	electric quantity of ES at node i in time t
S^{ES}_{max}, S^{ES}_{min}	electric quantity limits of ES at node i
$P^{\text{cha}}_{\max}$, $P^{\text{dis}}_{\max}$	the charging and discharging power limits
N_{T}	the charging and discharging times limit within a period
Υ	leakage constant of energy storage battery
χ	the simultaneity factor of spatial load
S_{j}, γ_{j}	the area and load density of land plot j (m^2, W/m^2)
χ^{2}_{c}, D_{c}	statistical thresholds of χ^{2} test and Kolmogorov–Smirnov K-S test
h_{opt}	the optimal bandwidth of kernel density estimation
C_{i}, c_{i}	CLUSTER i of vectors and the centroid of this cluster
v_{w}, v_{c}, v_{R}, v_{F}	real, cut-in, rated, and cut-out wind speeds
η, v_{s}	photovoltaic conversion efficiency and solar irradiance grade
N_{w}, N_{p}	number of WTGs and number of PV module
p_{w}, s_{pv}	rated power capacity of WTG and area of each PV module
T_{1}, T_{m}	average CPU time of the optimization run on 1 and m processors

variables of constructions and allocations of assets and the high number of continuous state variables of system operation. Comprehensive reviews of the solution methods for DSEP are given in [4,5]. Mathematical optimization methods such as linear mixed-integer programming [1], second-order cone programming [6], benders decomposition [7] and Branch and bound [8] have been observed to have potential issues of convergence and local optima trap. Evolutionary algorithms, e.g., genetic algorithm (GA) [9], particle swarm [10] and simulated annealing [11] are easy to use though they are subject to stochastic errors of solutions. Due to the growing scale and aggravating data-intensity and nonlinearity of DSEP, evolutionary algorithm has received increasing attention and developed into a mainstream for solving DSEP