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SÃO PAULO STATE UNIVERSITY
SCHOOL OF ENGINEERING
ILHA SOLTEIRA

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MULTISTAGE PLANNING FOR ACTIVE DISTRIBUTION SYSTEMS UNDER UNCERTAINTY: A COMPREHENSIVE APPROACH

Ilha Solteira
2023

JONATHAN PABLO AYALA MARCELO

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Thesis submitted to the School of Engineering of Ilha Solteira – UNESP in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Electrical Engineering.

Concentration Area: Electrical Engineering

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Potencial impact of this research

This research reduces the gap between the academic development and the practical applicability of solution approaches for the planning of electrical power distribution systems (a realistic and practical model together with a novel solution technique are proposed). Also, it is committed to sustainable development, proposing necessary actions to achieve optimal results while reducing carbon emissions.

Impacto potencial desta pesquisa

Neste trabalho de pesquisa propõe-se uma redução entre o desenvolvimento acadêmico e a aplicabilidade prática das abordagens de solução para o planejamento de sistemas de distribuição de energia elétrica (é proposto um modelo realista e prático juntamente com uma nova técnica de solução). Além disso, está comprometida com o desenvolvimento sustentável, propondo as ações necessárias para alcançar ótimos resultados e, ao mesmo tempo, reduzir as emissões de carbono.

Impacto potencial de esta investigación

Esta investigación reduce la brecha entre el desarrollo académico y la aplicabilidad práctica de los enfoques de solución para la planificación de sistemas de distribución de energía eléctrica (se propone un modelo realista y práctico junto con una técnica de solución novedosa). Además, apuesta por el desarrollo sostenible, proponiendo acciones necesarias para lograr resultados óptimos mientras se reducen las emisiones de carbono.

UNIVERSIDADE ESTADUAL PAULISTA

Câmpus de Ilha Solteira

CERTIFICADO DE APROVAÇÃO

TÍTULO DA TESE: MULTISTAGE PLANNING FOR ACTIVE DISTRIBUTION SYSTEMS UNDER UNCERTAINTY: A COMPREHENSIVE APPROACH

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This work is dedicated for all the people who have passed through my life leaving a mark, a memorable memory or simply a smile. Especially for my family.

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"Don't chase success, strive for excellence, and success will follow you."

(Rajkumar Hirani, 3 Idiots)

RESUMO

Neste trabalho propõe-se um novo modelo estocástico de dois estágios baseado em cenários para o planejamento multiestágio de sistemas ativos de distribuição de energia elétrica considerando um tratamento adequado das incertezas. O problema de planejamento é formulado como um modelo de programação quadrática inteira mista e resolvido mediante uma nova técnica matheurística que pode obter soluções de alta qualidade garantindo sua factibilidade em relação ao problema original (não linear e não convexo). Como o planejamento ótimo depende tanto da qualidade dos dados quanto da modelagem e da técnica de solução, os dados (parâmetros operacionais) e as incertezas são modeladas detalhadamente, considerando incertezas de curto e longo prazo. Propõe-se também um novo método para estimar as cargas dos veículos elétricos com base em distribuições de probabilidades. Para capturar a diversidade dos cenários de operação a partir das incertezas de demanda e recursos energéticos, preservando a transição temporal da operação do sistema (útil para a modelagem dos sistemas de armazenamento de energia elétrica), são utilizados cenários representativos de operação de duração diária e resolução horária. Para isso, é proposto um novo método para determinar cenários representativos robustos que permitem ênfase em cenários críticos, como aqueles de demandas máxima e mínima. Um grande portfólio de ações de planejamento é considerado visando obter o melhor plano de investimento com base nos recursos tecnológicos atuais, bem como investigar seus impactos na operação do sistema. Essas ações incluem repotencialização das subestações, instalação de comutadores de tap sob carga (OLTCs), sistemas de geração distribuída, sistemas de armazenamento de energia elétrica, bancos de capacitores fixos e chaveados, compensadores estáticos de reativos (SVCs), reguladores de tensão e recondutoramento. Adicionalmente, o modelo garante reduções periódicas de CO_2, para atender o compromisso de limitar o aquecimento global. Para ponderar adequadamente estas emissões, são contabilizadas as emissões de CO_2 provenientes da operação do sistema de distribuição e dos veículos a combustão, considerando a redução de emissões resultante da adoção dos veículos elétricos. Após o planejamento, a confiabilidade dos planos de investimento é analisada quantitativamente, mostrando as vantagens de considerar adequadamente as incertezas no processamento dos dados. Para demonstrar a eficácia do modelo proposto, são realizados testes em um sistema de distribuição de 69 nós e em um sistema real de 135 nós, considerando três estudos de casos com diferentes tratamentos de incerteza e diferentes seleções de cenários representativos.

Palavras-chave: Sistemas ativos de distribuição; incertezas; prosumidores; veículos elétricos; avaliação da confiabilidade do planejamento; matheurística.

ABSTRACT

This work proposes a new scenario-based two-stage stochastic model for the multistage planning of active distribution systems considering a proper handling of the uncertainties. The planning problem is formulated as a Mixed Integer Quadratic Programming (MIQP) model and solved through a matheuristic technique that can attain high-quality solutions guaranteeing their feasibility regarding the original non-linear and non-convex problem. Since an optimal planning depends on both data quality and modeling, due importance is given to data analysis (about operating parameters) and the uncertainties are modeled in detail, considering short and long term uncertainties. Also, a new method to estimate the Electrical Vehicle (EV) loads based on probability distributions is proposed. In order to capture the diversity of operation scenarios from demand and energy resource uncertainties while preserving the temporal transition of the system operation (useful for Electrical Energy Storage (EES) modeling), Representative Operating Scenarios (ROSs) of daily duration and hourly resolution are used. For that, a new method to determine robust ROSs is proposed, which allows to emphasize in critical scenarios, as those of maximum and minimum demand. A large portfolio of planning actions is considered with the aim of improving the system planning and investigating its impacts on system operation. These actions include substation replacement, installation of On Load Tap Changers (OLTCs), Distributed Generation (DG) systems, EES systems, fixed and switchable Capacitor Banks (CBs), Static VAr Compensators (SVCs), Voltage Regulators (VRs) and reconductoring. Moreover, the model guarantees periodical CO_2 reductions in order to be on track to limit global warming. To properly weight up these emissions, CO_2 emissions from distribution system operation and CO_2 emission reduction from EV adoption are accounted for. After planning, the reliability of the obtained investment plans are addressed and measured and the advantages of considering properly the uncertainties in data processing are shown. To show the effectiveness of the proposed model, tests are carried out in a 69-node distribution test system and a real 135-node distribution system, considering three case studies with different uncertainty handling and different selection of representative scenarios.

Keywords: Active distribution systems; uncertainties; prosumers; electrical vehicles; planning reliability assestment; matheuristics.

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LIST OF ACRONYMS AND ABBREVIATIONS

CB	Capacitor Bank
C&CG	Column-and-Constraint Generation
DISCO	Distribution Company
DG	Distributed Generation
DER	Distributed Energy Resource
EES	Electrical Energy Storage
EV	Electrical Vehicle
EVCS	Electric Vehicle Charging Station
HMM	Heuristic Moment Matching
KKT	Karush-Kuhn-Tucker
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MISOCP	Mixed Integer Second Order Cone Programming
MICP	Mixed Integer Conic Programming
MIQP	Mixed Integer Quadratic Programming
NSGA-II	Non-Dominated Sorting Genetic Algorithm
O&M	Operation and Maintenance
OLTC	On Load Tap Changer
OPF	Optimal Power Flow
PDF	Probability Density Function
PWL	Piece-Wise Linearization
QP	Quadratic Programming
ROS	Representative Operating Scenario
SOC	State of Charge
SVC	Static VAr Compensator

TSO	Transmission System Operator
VR	Voltage Regulator

LIST OF SYMBOLS

Index sets and indices

Ω_B,Ω_{B^+},(i,j)	Index set/index of branches/branches including transformer windings.
Ω_N, i, j, j'	Index set/indices of nodes.
$\Omega_{\bar{N}}, \Omega_{ss}$	Index set of load/substation nodes.
Ω_B^{vr}	Index set of candidate branches to install VRs.
Ω_{ees},Ω_{pv},Ω_{wd}	Index set of candidate nodes to install EES/photovoltaic (PV) DG/wind DG systems.
Ω_{rc}	Index set of candidate nodes to install reactive compensation devices.
Ω_C, a, a';	Index set/indices of conductor/support types
Ω_{sp}, e, e'	for reconductoring.
$\Omega_{\overline{ss}}, u$	Index set/index of substation types.
Ω_{vr}, v	Index set/index of VR types.
Ω_V, v	Index set/index of EV charging levels.
Ω_T, t, t'	Index set/indices of planning periods.
Ω_Y, y	Index set/ index of years of each planning period.
Ω_D, d	Index set/index of days within a year.
Ω_H, h	Index set/index of hours within a day.
Ω_R^t, r	Index set/index of representative operating scenarios.

Planning and investment parameters

$c_{a',a}^{cr}$	Investment cost for the replacement of type a' conductor by type a (\$/km).
$c_{e',e}^{sp}$	Investment cost for the replacement of type e' structure by type e (\$/km).
$c_{t,h}^{en}$	Cost of energy supplied by the substation (\$/kWh).
c_f^{fcb}, c_v^{fcb}	Fixed/Variable investment cost of fixed CBs (\$).
c_f^{scb}, c_v^{scb}	Fixed/Variable investment cost of switchable CBs (\$).
$c_t^{ees}, com_{t,y}^{ees}$	Investment/O&M cost of EES systems (\$/kW).
$c_t^{pv}, com_{t,y}^{pv}$	Investment/O&M cost of PV systems (\$/kW).
$c_t^{wd}, com_{t,y}^{wd}$	Investment/O&M cost of wind systems (\$/kW).
c_t^{svc}	Investment cost of a SVC (\$).
$c_t^{ss,k}$	Investment cost of substations (\$).
$c_t^{vr,v}$	Investment cost of VR units (\$).
$n_T, n_Y, n_{t,y}$	Number of planning periods/of years of each planning period/of years until planning period t and year y inclusive.

ι	Annual discount rate.
T, T_t	Planning horizon/time span from the beginning of planning period t (years).
β_t^{inv}	Present value factor for investments.
$\beta_{t,y}^{en}$	Present value factor for energy purchase.
$\beta_{t,y}^{om}$	Present value factor for O&M costs.
ω_t^{as}	Use factor for asset as.

Distribution network parameters

$a_0^{i,j}/e_0^{i,j}$	Initial conductor/ structure type of line (i,j).
$\mathrm{p}_{ss}^{ind}/\mathrm{p}_{ss}^{cap}$	Minimum inductive/capacitive power factor allowed at substations.
$\bar{I}_a$	Nominal current of type a conductor.
$(i,j)_c/(i,j)_s$	Existing conductor/supports of branch (i,j).
$l_{i,j}$	Length of line (i,j) (km).
R_a, X_a, Z_a	Resistance/Reactance/Impedance of type a conductor (Ω/km).
$R_{ss}^i, X_{ss}^i, Z_{ss}^i$	Equivalent resistance/reactance referred to secondary of the power transformers (Ω).
L_{ss}^i	No-load losses of the power transformers (kW).
ss_i	Existing substation at node i.
$S_0^{ss,i}$	Nominal power of the existing substations (kVA).
T_{as}, T_{as}^0	Lifespan/Elapsed life until the beginning of the planning horizon of system asset as.
$\overline{V}, \underline{V}$	Upper/Lower voltage limit.

Parameters related to operating parameters

c_{ev}	EV energy consumption rate (kWh/km).
$\dot{\mathrm{f}}_{t,d,h}^D, \dot{\mathrm{f}}_{t,d,h}^R$	Active/Reactive power demand factor.
$\mathrm{f}_{t,d,h}^D, \mathrm{f}_{t,d,h}^R$	Active/Reactive power demand factor for representative days.
$\bar{\ell}, \ell_d$	Average/Day-d commute route length (km).
$\bar{n}^{ev}, n_0^{ev}$	Number of EVs over all the planning horizon/at the beginning of the planning horizon.
$n_{t,y}^{ev}, n_{t,y}^{ev,i}$	Number of EVs powered by the system/by the node i.
$n_{t,y}^{v,i}$	Number of vehicles within node i area, in period t and year y.
$N_0^{v,i}$	Number of EVs present at the beginning of the planning horizon.
$\hat{\mathrm{p}}_{pr}$	Power factor of DG systems owned by prosumers.
p_{ev}	Power factor of EV chargers.
p_v	EV charging power.
$P_{0,d,h}^{cd,i}, Q_{0,d,h}^{cd,i}$	Estimated active/reactive conventional demand at the beginning of the planning horizon (kW/kVAr).

$\bar{P}_t^D, \bar{Q}_t^D$	Maximum active/reactive system power demand (kW).
$\bar{P}_{t,d}^{D,i}, \bar{Q}_{t,d}^{D,i}$	Maximum active/reactive power demand of node i on representative day d (kW).
$\dot{P}_{t,y,d,h}^{D,i}, \dot{Q}_{t,y,d,h}^{D,i}$	Total active/reactive power demand (kW/kVAr).
$P_{t,y,d,h}^{D,i}, Q_{t,y,d,h}^{D,i}$	Total active/reactive power demand of representative days (kW/kVAr).
$P_{\mu,h}^{ev}$	Diversified EV load (kW).
$P_{t,y,d,h}^{ev,i}, Q_{t,y,d,h}^{ev,i}$	Active/Reactive expected load of the EV fleet powered by node i (kW/kVAr).
$P_{t,y,d,h}^{pr,i}, Q_{t,y,d,h}^{pr,i}$	Active/Reactive power output of prosumers' DG systems (kW/kVAr).
soc_{min}	Minimum State of Charge (SOC) value needed to complete an EV daily trip.
$\alpha_{t,v}^{ev}, \phi_{t,v}^{ev,i}$	Percentage of EV owners who have access and prefer charging their EVs with charging level v/with charging level v at node i.
$\lambda_{t,y}^{ev,i}/\lambda_{t,y}^{pr,i}$	EV/Prosumers' DG penetration.
$\varsigma^{p,i}, \varsigma^{q,i}$	Annual growth rate of active/reactive conventional demand at the beginning of the planning horizon.
τ_i^{ev}/τ_i^{pr}	Expected date of maximum EV penetration/prosumer penetration (year).

Parameters associated to planning actions

$\dot{\mathrm{f}}_{t,d,h}^{pv}, \dot{\mathrm{f}}_{t,d,h}^{wd}$	PV/wind generation factor.
$\mathrm{f}_{t,d,h}^{pv}, \mathrm{f}_{t,d,h}^{wd}$	PV/wind generation factor for representative days.
$\bar{I}_{vr,v}$	Nominal capacity of a type v VR.
m_{max}^{cb}	Maximum number of modules that can be integrated in a capacitor bank.
$n_{max}^{wd,i}$	Maximum number of wind system units that can be installed at node i (kW).
n_{tap}	Number of positions of an OLTC.
$\mathrm{p}_{pv}^{ind}/\mathrm{p}_{pv}^{cap}$	Minimum inductive/capacitive power factor allowed in PV systems.
$\mathrm{p}_{wd}^{ind}/\mathrm{p}_{wd}^{cap}$	Minimum inductive/capacitive power factor allowed in wind systems.
$P_{max}^{pv,i}$	Maximum PV system nominal power that can be installed at node i.
$P_{t,d,h}^{+ees,i}/P_{t,d,h}^{-ees,i}$	Power delivered by EES system to the grid/ vice versa, at node i, year t, representative day d, hour h (kW).
$\hat{P}_t^{pr}$	Total installed power by prosumers at node i.
$\bar{P}_{\mu}^{ees}$	Nominal capacity of an EES system unit.
P_{μ}^{wd}	Nominal power of a wind system unit (kW).
Q_{μ}^{cb}	Nominal capacity of an unitary module of capacitor banks (kVAr).
soc_{min}^{ees}	Minimum charge allowed in EES systems (%).
$S^{ss,k}$	Nominal power of a type k substation (kVA).
$\pm v_R$	Regulation range of VRs (p.u.).
$\overline{V}_{t,d,h}^{i'}$	Primary voltage of substation transformers (p.u.).
$\eta_{ch}^{ees}/\eta_{dch}^{ees}$	Charging/ Discharging efficiency of EES systems.
κ	Storage duration of EES systems (h).

Parameters associated to CO_2 emissions

n_t^{cv}	Expected number of combustion vehicles to be replaced by EVs until the end of period t.
n_t^{ev}, n_0^{ev}	Expected number of EVs present at the end of planning period t/Number of EVs at the beginning of the planning horizon.
r_{co_2}	Carbon rate (\$/kg CO_2).
$\alpha\%$	Reduction of CO_2 emissions required for each planning period.
$\gamma\%$	CO_2 intensity reduction of the energy supplied by substations.
$\Gamma_{t,h}^{co_2}$	Average hourly CO_2 intensity of the energy supplied by substations in period t (kg CO_2/kWh).
$\varepsilon_{cv}^{co_2}$	Average CO_2 emission of an engine combustion vehicle (kg CO_2/km).
$\xi_{S,0}^{co_2}$	Average annual CO_2 emissions from distribution system for a period precedent to the planning (kg CO_2).
$\xi_{cv,0}^{co_2,t}$	Annual CO_2 emissions from the combustion vehicles expected to be replaced by EVs until the end of planning period t (kg CO_2).

Parameters associated to the solution technique

g_I	Maximum optimality gap allowed.
k	Iteration index.
(P^*, Q^*, V^*, I^*)	Reference operating point.
$(P^{ss,*}, Q^{ss,*})$	Reference operating point of substations.
$(P, Q, V)_k^{inc}$	Incumbent solution at iteration k.
M_1, M_2, M_3	Feasibility error coefficients.
$\varepsilon_R, \varepsilon_S$	Maximum feasibility error allowed for the relax stage/solution.
ξ_{feas}	Feasibility error (kVA).

Continuous variables

$c_t^{fcb,i}/c_t^{scb,i}$	Investment cost required for fixed/ switchable CBs.
$c_t^{wd,i}$	Investment cost required for wind systems.
$\bar{E}_t^{ees,i}, \bar{P}_t^{ess,i}$	Total energy storage capacity (kWh)/Total rated power (kW) of EES systems.
$E_t^{ees,i}, P_t^{ess,i}$	Energy storage capacity (kWh)/Rated power (kW) of EES systems installed in period t.
$E_{t,0}^{ees,i}$	Initial charge of EES systems.
$I_{t,d,h}^{i,j}$	Square of branch current.
$P_{t,d,h}^{i,j}, Q_{t,d,h}^{i,j}$	Active/Reactive power flow.
$P_{t,d,h}^{+ees,i}, P_{t,d,h}^{-ees,i}$	Power delivered/received by EES systems.
$\bar{P}_t^{pv,i}, \bar{P}_t^{wd,i}$	Total PV/wind system capacity.

$P_t^{pv,i}, P_t^{wd,i}$	PV/wind system capacity installed in period t.
$P_{t,d,h}^{pv,i}, P_{t,d,h}^{wd,i}$	Active power supplied by PV/wind systems.
$P_{t,d,h}^{ss,i'}, Q_{t,d,h}^{ss,i'}$	Active/Reactive power supplied at the primary terminals of the substation transformers.
$Q_{t,d,h}^{cb,i}$	Reactive power supply by CBs.
$Q_{t,d,h}^{svc,i}$	Reactive power supply by SVCs.
$Q_{t,d,h}^{pv,i}, Q_{t,d,h}^{wd,i}$	Reactive power supplied by PV/wind systems.
$V_{t,d,h}^{i}$	Nodal voltage squared.
$\Delta V_{t,d,h}^{i}$	Regulation of nodal voltage squared.
$\Delta_{t,d,h}^{i,j}$	Linearization control variable.
$\xi_{S,t}^{co_2}, \xi_{cv,t}^{co_2}$	Expected annual CO_2 emissions from system operation/combustion engine vehicles (kg CO_2).

Integer variables

$\bar{m}_t^{fcb,i}, \bar{m}_t^{scb,i}$	Number of modules of the fixed/switchable CB allocated at node i.
$m_{t,d,h}^{scb,i}$	Number of active modules of the switchable CB allocated at node i.
$n_t^{ees,i}$	Number of EES system units installed at node i.
$n_t^{wd,i}$	Number of wind turbines installed at node i.
$tap_{t,d,h}^{i}$	Tap position of the OLTC installed at node i.

Binary variables

$x_t^{a,i,j}, z_t^{e,i,j}$	State variable that indicates if the conductor/structure of line (i,j) have been replaced by one of type *a*/*e*.
$x_t^{fcb,i}, x_t^{scb,i}$	Decision variable for fixed/switchable CB installation.
$x_t^{oltc,i}, x_t^{ss,u,i}$	Decision variable for OLTC/type u substation installation.
$x_t^{svc,i}$	Decision variable for SVC installation.
$x_t^{wd,i}$	Decision variable for wind system installation.
$\varkappa_t^{v,i,j}$	Decision variable for VR installation.
$\varkappa_t^{i,j}$	State variable that indicates that a VR has been installed.

Random variables

$\tilde{\mathrm{f}}_{d,h}^{pv}, \tilde{\mathrm{f}}_{d,h}^{wd}$	PV/Wind generation factor.
$\tilde{h}_v^{in}, \tilde{h}_v^{fi}$	Charging start time/end time.
$\tilde{n}_{t,y}^{ev,i}$	Number of EVs.
$\tilde{P}_{t,y,d,h}^{cd,i}, \tilde{Q}_{t,y,d,h}^{cd,i}$	Active/Reactive conventional demand (kW/kVAr).
$\tilde{P}_{t,y,d,h}^{ev,i}, \tilde{Q}_{t,y,d,h}^{ev,i}$	Active/Reactive EV load (kW/kVAr).
$\tilde{P}_{t,y,d,h}^{pr,i}, \tilde{Q}_{t,y,d,h}^{pr,i}$	Active/Reactive power generated by prosumers (kW/kVAr).
$s\tilde{o}c_d^{in}, s\tilde{o}c_d^{fi}$	EV battery SOC at the charging start/at the end of charging .

$\tilde{x}_d$	EV charging decision.
$\tilde{z}^{s,i,h}_{cd,p}, \tilde{z}^{s,i,h}_{cd,q}$	Short-term uncertainty related to hourly active/reactive demand.
$\tilde{z}^{\ell,t}_{cd}$	Long-term uncertainty related to demand growth.
$\tilde{z}_{ev}$	Uncertainty related to the date of maximum EV penetration.
$\Delta\tilde{h}_d$	Charging duration (h).
$\tilde{\tau}^{ev,i}, \tilde{\tau}^{pr,i}$	EV/Prosumer peak penetration date (years).

Operators and symbols

$\mathbb{E}(x)$	Expected value of the random variable x.
$\lfloor n \rceil$	Rounding of n to the nearest integer.
$\langle s \rangle$	Logical value (0,1) of statement s.
∂	Customized metric used in K-means.
$:=$	Equal by definition.
$\|x\|^*$	Euclidean norm column by column of matrix x.
$[x]_{\Omega_1,..\Omega_n}$	Array indexed by the ordered sets $\Omega_1, ..\Omega_n$.

CONTENTS

1 INTRODUCTION

The operation of distribution systems is facing significant changes due to the increasing participation of Distributed Energy Resources (DERs), as DG and EES systems (owned by prosumers, independent agents or Distribution Companies (DISCOs)), and the increasing adoption of EVs. These changes include the presence of bidirectional power flows, increased demand variability (usually translated into duck curves) and increased operating uncertainty. In this context, the traditional distribution systems are turning into active distribution systems for both taking advantage of the DER capabilities and dealing with their adverse effects. Here, note that active distribution systems are those that include in their infrastructure systems capable of controlling their distributed energy resources (ADAMO *et al.*, 2011), and also other system assets, as OLTCs, CBs, SVCs and VRs. On the one hand, this feature allows the system to be operated more flexibly and efficiently and it points to investment plans that lead to cheaper distribution and energy costs compared with that for traditional systems. On the other hand, determining the optimal investment plan becomes a more challenging task, since more variables are involved in the planing problem while uncertain operating conditions need to be handled.

Planning actions, typically, have involved the allocation of capacitor banks for reactive compensation (SUNDHARARAJAN; PAHWA, 1994), the installation of voltage regulators at critical points of the network for voltage regulation (SAFIGIANNI; SALIS, 2000), and reconductoring to upgrade the power capacity of selected lines while reducing both power losses and voltage drops (FRANCO *et al.*, 2013). Subsequently, with the emergence and adoption of DG, the planning problem shifted its focus to the optimal allocation and sizing of DG systems within the grid (GEORGILAKIS; HATZIARGYRIOU, 2013), as well as to an integrated planning, considering also the typical planning actions previously mentioned (SHAHEEN; EL-SEHIEMY, 2021). The participation of prosumers has been studied in the field of smart grids with the aim of managing DG systems units and other DERs owned by prosumers (normally through an agregator) to reduce their electricity bills while improving system operational flexibility (HU *et al.*, 2021). However, prosumer participation has not been yet considered in the context of distribution system planning. Since prosumers are increasing rapidly to levels capable to affect the normal system operation, their participation is considered in this work.

Regarding system planning objectives, traditionally they consisted of minimizing investment and operating costs as well as improving efficiency and reliability (VAHIDINASAB; MEMBER; TABARZADI, 2020). In recent years, due to the urgent need to reduce the global warming and promoted by Kyoto Protocol (1997) and Paris Agreement (2015), reducing CO_2 emission has become a novel and significant objective of the planning problem (ZENG *et al.*, 2014). This has led to several actions, such as, increased participation of renewable DG (mainly PV and wind) (MELGAR-DOMINGUEZ; POURAKBARI-KASMAEI; MANTOVANI, 2019); the development and application of emission abatement polices, such as cap and trade, and carbon taxes (POURAKBARI-KASMAEI *et al.*, 2020); the modeling and integration of EVs into the distribution network (SHA; FOTUHI-FIRUZABAD, 2013); and a greater interest in determining and increasing renewable DG hosting capacity (CAPITANESCU *et al.*, 2015). About the last point, note that the integration of EES systems into the grid stands out as a plausible solution, which also improves the flexibility and reliability of system operation (JAYASEKARA *et al.*, 2016).

The distribution planning, in short, involves currently the following planning actions: construction or upgrade of substations, installation of OLTCs to regulate the substations voltages, allocation of fixed and switchable CBs as well as SVCs for reactive compensation, installation of voltage regulators at critical points of the network, reconductoring to upgrade the power capacity of selected lines while reducing both power losses and voltage drops, allocation and sizing of DG systems and installation of EES systems to increase the DG hosting capacity while improving system flexibility (XIE *et al.*, 2018; MELGAR-DOMINGUEZ; POURAKBARI-KASMAEI; MANTOVANI, 2019; MEJIA *et al.*, 2022). In order to obtain the optimal investment plan, ideally, all the available planning actions should be considered in the problem modeling, however, since this involves a high computational burden for the traditional solution approaches, it has not yet been addressed in the existing literature. Thus, the present work aims to cover this gap.

Currently, to address the planning problem, three different techniques can be used: Mathematical programming, metaheuristics and matheuristics (BOSCHETTI; MANIEZZO, 2022). In general, the planning problem can be accurately formulated as a non-convex Mixed Integer Non-Linear Programming (MINLP) model, but this model correspond to a NP-hard problem, even undecidable for some cases, and extremely difficult and computationally expensive to solve in practice (BELOTTI *et al.*, 2013). Thus, to get around these issues, the mathematical programming approaches use convex relaxations or approximations to model the problem. Hence, conic relaxation and Piece-Wise Linearization (PWL) are widely used, leading to Mixed Integer Second Order Cone Programming (MISOCP) and Mixed Integer Linear Programming (MILP) models, respectively (HAGHIGHAT; ZENG, 2018; TABARES *et al.*, 2016). The main feature of these techniques is their ability to obtain the global optimum of their models. However, they can not guarantee that their solutions are feasible for the original planning problem. Additionally, these techniques are usually too computationally expensive (and sometimes not suitable) for large-scale problems. On the other hand, metaheuristics are a good option to provide feasible solutions in relative short times, what makes them appropriate for large problems (ARASTEH *et al.*, 2016); but they neither recognize global optimality nor provide a measure to indicate the proximity to the optimal solution of the problem. Finally, matheuristic is a relative new term that refers to heuristic algorithms based on mathematical programming. Generally, this technique solves a series of sub-problems formulated according to a given metaheuristic via mathematical programming (BOSCHETTI; MANIEZZO, 2022; HOME-ORTIZ *et al.*, 2020). Matheuristics are supposed to be computationally less expensive than mathematical programming and has the advantage over metaheuristics that it can guarantee the optimality of the addressed sub-problems, thus, the obtained solution is likely to be a high-quality local optimal. Hence, in order to attain feasible and high-quality solutions in a reasonable computational time, the present work proposes a novel solution technique based on a matheuristic approach.

Distribution system planning aims at allowing safe and sustainable operation of the system under different operating conditions at minimum cost. Compared with traditional network operation, the variability of the operating conditions of modern distribution systems has increased significantly mainly due to the increasing penetration of prosumers and EVs. Thus, the variability and uncertainty from PV generation (prosumers) and EV loads are more and more noticeable in the load profiles. Additionally, medium and large renewable DG systems owned by independent agents or DISCO makes the operation system dependent to some degree of the energy resources variations (solar irradiation and wind). In this context, the modeling of the variation and uncertainty from demand (conventional and EVs) and renewable energy resources are of special interest for the planning of modern distribution networks, and even more if the planning is long-term because it adds forecast uncertainty to the modeling. In order to address the planning problem considering the variable and uncertain operation of the system, optimization-under-uncertainty methods are used in the literature (ROALD *et al.*, 2023). Due to the large quantity of random variables involved in the system operation and the large-scale nature of the planning problem, this work use the two-stage stochastic optimization method on a finite set of representative scenarios.

The random variables associated to system operation are of continues type, therefore, the number of their realizations is infinite. Thus, in order to get a solvable model in the context of scenario-based two-stage stochastic optimization, a finite set of representative realizations is required (ROALD *et al.*, 2023). From this point it follows that the quality of the solution is strongly related to the selection of that representative realizations (scenarios). In this way, there is no use finding the global optimal of a problem based on no-representative scenarios. Therefore, the data analysis and selection is as important as the formulation and solution technique of the planning problem. The two-stage stochastic optimization method is widely used in distribution system planning, but most of the works from literature only consider the historical data and their expected forecasts leaving aside the associated uncertainty (EHSAN; YANG, 2020a; XIE *et al.*, 2018; LIMA *et al.*, 2022; MEJIA *et al.*, 2022), which can lead to get representative scenarios that do not really represent all (of most of) the possible realizations of uncertainties. The impact of this fact can be visualized with a simple example: consider that two different instances of a variable are represented by normally random variables, e.g., $n_{t_1} \sim \mathcal{N}(4,4)$ and $n_{t_2} \sim \mathcal{N}(7,9)$. If K-means clustering with $K = 2$ is performed over those variable instances, the obtained representative values are 3.56 and 8.48. In contrast, if the random nature of the variables is ignored the result will correspond to their expected values (4 and 7), losing data variability, which is an important feature for planning purposes. Thus, this work models in detail the uncertainty from operating parameters and obtains the representative scenarios on a large set of realizations of that uncertainty.

In this work, a novel multistage planning model for active distribution systems under uncertainty is proposed. The work addresses properly the operating uncertainty and proposes a customized K-means clustering especially designed for planning purposes (in the context of scenario-based two-stage stochastic programming). Also, a post-planning stage to address and measure the planning reliability is proposed. Additionally, this work considers important practical planning and operating aspects not addressed before in the existing literature (to the best of the author's knowledge), such as the elapsed life of the existing system assets (as substations, conductors and supports), the increasing penetration of both prosumers and EVs and the losses in substation transformers.

1.1 LITERATURE REVIEW

Developing an optimal planning for distribution systems is of utmost interest to all involved agents, such as consumers, DISCOs and society. This is because a proper planning results in reduced investments and operational costs, leading to lower electricity rates, as well as in improved energy efficiency and reduced greenhouse gas emissions. Therefore, the distribution system planning problem is an important topic in both industry and academia, and it has been widely discussed in the specialized literature considering different approaches in terms of mathematical models, objectives and solution techniques. Thus, relevant works about distribution system planning are discussed below, with focus on those related to multistage planning for active distribution systems under uncertainty.

Pereira, Cossi and Mantovani (2013) propose a multi-objective short-term model for the planning of electric power distribution systems. The model corresponds to a MINLP model and it is solved through the metaheuristic Non-Dominated Sorting Genetic Algorithm (NSGA-II). The problem objective is minimize the investment and operating costs as well as the voltage magnitude deviations in the network buses. For that, the installation of CBs, VRs and reconductoring are considered as planning actions. This work shows that nonlinearities from the objective and constraints of the model can be successfully handle through metaheuristics to obtain feasible solutions. However, it can not be informed how close is the solution from the global optimal.

Tabares *et al.* (2016) propose a multistage long-term expansion planning of electrical distribution systems considering multiple planning actions. The planning problem is modeled as a MILP model based on PWL technique. The planning actions include increasing the capacity of existing substations, constructing new substations, allocating capacitor banks, voltage regulators, DG systems , constructing or reinforcing circuits, and modifying the system topology. The work presents six case studies that include, independently and then jointly, the participation of CBs, VRs and DGs. However, the variation and uncertainty from the operating parameters within each planning period are not considered.

Xie *et al.* (2018) propose a multi-objective and scenario-based stochastic programming model. The model uses uncertain random network theory in order to take into account the uncertainty associated with the reliability and stability of distribution lines. For the operating parameters, demand and renewable-based energy resources, the uncertainty is modeled through representative scenarios obtained as the combinations of individual representative values of each parameter. Thus, the temporal correlation among the operating parameters is not preserved. The model includes the installation of OLTCs for voltage regulation in substations and SVCs for reactive power compensation. The model is formulated using a conic relaxation as a MISOCP model. Then, the accuracy of the results regarding the original MINLP model is evaluated. It is shown that, due to the negligible errors obtained in the conic relaxation for the employed test system, the solution found with the MISOCP model corresponds to the solution of the original MINLP model, corresponding therefore to the global optimal. Thus, the MISOCP can led to global optimality occasionally, but in fact, this is unusual in the context of modern distribution system planning.

Arias *et al.* (2018) propose a chance-constraint MILP model for the expansion planning that guarantees that substations do not operate above their nominal capacity within a specified confidence level. For that, the uncertainties from conventional and EV demand are considered and modeled as normally distributed variables. The MILP model is obtained through the PWL of the squares of the active and reactive powers present in the operating constraints. Also, the model considers the increasing penetration of EVs and the installation of Electric Vehicle Charging Stations (EVCSs) over the planning horizon. However, the participation of prosumers is not considered. Finally, the compliance of the preset confidence level is verified through Monte Carlo simulations.

Melgar-Dominguez, Pourakbari-Kasmaei and Mantovani (2019) present a two-stage robust optimization model for the short-term planning. The system parameters are modeled using a representative day for each season, which allows to model properly the EES transition, but since it does not take into account the correlation among the operating parameters, the obtained representativeness is not necessarily the best. The uncertainties of demand and renewable power output factors are modeled through uncertainty intervals built based on normal probability distributions within a confidence level of 95%. The two-stage robust model is formulated as a bilevel optimization model that then is recast to a single-level MILP model through Karush-Kuhn-Tucker (KKT) optimality conditions. Since the joint use of PWL and KKT conditions is not appropriate for optimality, a linearization based on Taylor series is proposed. Finally, the problem is solved applying the Column-and-Constraint Generation (C&CG) algorithm.

Home-Ortiz *et al.* (2020) propose a matheuristic approach based on a Mixed Integer Conic Programming (MICP) model to address the expansion planning. The proposal shows that a matheuristic approach can perform better than solving the original MICP problem via mathematical programming. However, it is worth indicating that since the model is based on a conic relaxation, the feasibility of the original MINLP planning problem is not guaranteed. To handle the uncertainties, the model is formulated as a scenario-based two-stage stochastic programming model and the uncertainties from demand, solar irradiation and wind speed are addressed trough representative scenarios obtained via k-means clustering on historical data. The matheuristic approach used to solve the problem consist of the joint application of MICP and the philosophy of the meta-heuristic Variable Neighborhood Descent (VND).

Ehsan and Yang (2020a), Ehsan and Yang (2020b) propose a scenario-based stochastic model formulated as a MILP model for the multistage joint reinforcement planning of distribution systems and EVCSs. The work uses a Markov-based approach to model the EV charging demand and the Heuristic Moment Matching (HMM) method to generate representative scenarios based on historical data of wind and PV generation, conventional demand and expected EV demand. The HMM method aims at preserving the first four stochastic moments of historical scenarios, i.e., expectation, standard deviation, skewness and kurtosis. Thus, reliable representative scenarios regarding the historical data are expected to be obtained. However, since uncertainties are not considered, some information could be missing. Additionally, the work evaluates the expansion planning solution in terms of failure rate of substation capacities through Monte Carlo simulations.

Lima *et al.* (2022) present a scenario-based stochastic MILP model for the long-term expansion planning. This work proposes a method to estimate and generate EV load profiles for one year range. Representative scenarios are obtain through the application of k-means clustering on historical data of demand, solar irradiation and wind speed, in addition to the EV load profiles previously generated. The model considers the installation of EES systems as planning action. Since their current prices do not favor their participation on the investment plans, a sensitivity analysis for different EES system prices is performed in order to investigate the instances in which installing EES systems will be required (being the best option). The reactive power is supplied only by substations and DG systems. Thus, reactive compensation equipment are not considered. Additionally, in this work is stated that the investment plans obtained by the proposed MILP model are the same of those obtained by solving the original MINLP problem (possibly by a non-linear solver).

Mejia *et al.* (2022) propose a scenario-based stochastic MILP model to address the multistage planning of active distribution systems. The model includes EVCS installation, several planning actions and voltage-dependent load behavior. The EV charging demand is estimated by zones based on real travel patterns and assumptions about when and where EVs should be charged. The work considers five uncertain parameters: demand, wind speed, solar irradiation, energy prices, and EVCS loads. Representative scenarios are obtained from historical data. This data is classified in sub-groups by season and day/night, then the algorithm k-means++ is applied to each sub-group. The model assumes that there is an environmental policy that penalizes excess of CO_2 emissions from the distribution system. Thus, CO_2 emission limits are imposed in order to prevent penalties for excess emissions. However, the CO_2 emission reduction from EV adoption (through the replacement of combustion vehicles) is not considered.

Finally, it is worth indicating that important aspects about the planning and operation of distribution systems have not yet been addressed in the existing literature, such as the elapsed life of the existing system assets (as substations, conductors and supports), the mechanical correlation between conductors and supports and the losses of substation transformers. Also, the increasing penetration of prosumers has not been considered in the long-term planning. Another important point is that the works that use scenario-based two-stage stochastic programming only take into account expected values of the operating parameters, overlooking their associated short-term and long-term uncertainty. Additionally, about the solution approaches used to solve the planning problem, it is observed that most of the existing works do not take care of guaranteeing the feasibility of solution regarding the original MINLP problem, which can lead to pseudo-solutions with significant errors as shown in (MARCELO *et al.*, 2023).

1.2 OBJECTIVES

The main goal of this work is obtaining a realistic planning model for active distribution systems in order to determine the investment plan to be executed in the short-term (knowing the possible future operating scenarios) and anticipate the future investment actions and the network operation to prevent possible issues or improve certain operating or policy aspects. Aiming to fulfill this goal the following objectives are established.

- Propose a multistage planning model for active distribution systems considering the operating uncertainty.

- Propose a solution technique to solve the planning problem aiming to obtain the global optimal solution or high-quality local solutions guaranteeing the feasibility regarding the original problem (non-linear and non-convex). This solution technique must solve the planning problem in adequate computational times for practical purposes and must perform well for large problems involving a high number of discrete variables.
- Model the operating uncertainty in a proper and detail way in such a manner that it allows generating realistic operating scenarios as the realizations of that uncertainties.
- Include important and realistic aspects about the planning and operation of distribution systems in the optimization model in order to represent the system as realistically as possible and convenient.
- Assess the reliability of the obtain investment plans in order to verify or, if necessary, modify the investment decisions.

1.3 CONTRIBUTIONS

The main contributions of this work are summarized as follows. Additionally, the novelties of this work regarding the state of the art are presented in Tables 1 and 2.

- A new scenario-based two-stage stochastic model for the multistage planning of active distribution systems under uncertainty is proposed. The model considers the data uncertainty and not only their expected forecast values as done in previous related works. This leads to investment plans that better withstand uncertainty.
- A novel solution technique for the planning problem is proposed, which can obtain high-quality local optimal solutions in relative short times guaranteeing its feasibility regarding the original non-convex MINLP planning problem. The application of this technique allows to solve the planning problem considering a large portfolio of planning actions and several scenarios over a broad planning horizon.
- A detailed modeling of the operating parameters under uncertainty is proposed. The modeling includes short-term uncertainties related to the realization of a random variable in a given time and long-term uncertainties related to the growth forecast of conventional demand, prosumers and EVs over the planning horizon.
- The planning modeling considers the elapsed life of existing assets in decision making, which in practice is a determining factor to decide the optimal timing of assets replacement or installation. To the best of the author's knowledge this topic is addressed for the first time in the existing literature.

Table 1 – Comparison of this work with the state of art - part 1

Reference	System modeling					Solution technique						
						Approach	Solution quality[1]					
	Assets elapsed life	Prosumers	EVs	EES temporal transition	CO_2 reduction		Global optimum	Local optimum	Approximate solution	Lower bound	Upper bound	Feasible
Pereira, Cossi and Mantovani (2013)	✕	✕	✕	✕	✕	Metaheuristic (NSGA-II)	✕	✕	✕	✕	✓	✓
Tabares et al. (2016)	✕	✕	✕	✕	✕	MP (MILP)	✕	✕	✓	✕	✕	✕
Xie et al. (2018)	✕	✕	✕	✕	✕	MP (MISOCP[2])	✕	✕	✓	✓	✕	✕
Arias et al. (2018)	✕	✕	✓	✕	✕	MP (MILP)	✕	✕	✓	✕	✕	✕
Melgar-Dominguez, Pourakbari-Kasmaei and Mantovani (2019)	✕	✕	✕	✓	✕	MP (C&CG MILP)	✕	✕	✓	✕	✕	✕
Home-Ortiz et al. (2020)	✕	✕	✕	✕	✓	MP (MICP)	✕	✕	✓	✕	✕	✕
Ehsan and Yang (2020a) Ehsan e Yang (2020b)	✕	✕	✓	✕	✕	MP (MILP)	✕	✕	✓	✕	✕	✕
Lima et al. (2022)	✕	✕	✓	✕	✓	MP (MILP)	✕	✕	✓	✕	✕	✕
Mejia et al. (2022)	✕	✕	✓	✕	✓	MP (MILP)	✕	✕	✓	✕	✕	✕
This work	✓	✓	✓	✓	✓	Matheuristic (MIQP)	✕	✓	✕	✕	✓	✓

[1] regarding the original non-convex MINLP planning model, [2] occasionally can attain global optimality, but it can not recognize or prove it by itself
MP: Mathematical Programming, ✓: considered, ✕: not considered

Source: Elaborated by the author.

- A new methodology to estimate and generate EV load profiles is proposed, considering different charging levels and preferences about charging schedules.
- The impact of using different representative scenarios on planning reliability is analyzed. Also, it is proposed a new method to determine representative scenarios that aim to improve the planning reliability.

1.4 DOCUMENT STRUCTURE

This work, in addition to its introductory chapter, is organized as follows:

In Chapter 2, the system operating parameters are modeled under uncertainty. This includes the modeling of conventional demand, EV loads and DG systems (including prosumers). Then, the integration of these parameters is done while presenting the generation of system operating scenarios.

In Chapter 3, the formulation for the planning problem is proposed. At first, the use of ROSs is addressed and a new method to determine them (in order to improve the planning reliability) is proposed. Then, the objective function and the constraints of optimization model (corresponding to the planning problem) are presented and justified.

Table 2 – Comparison of this work with the state of art - part 2

Reference	Planning features										
	Uncertainty approach	Planning actions									Planning reliability assessment
		Substation update	OLTC	Re-conductoring	CBs		SVC	VR	DG	EES	
					Fixed	Switchable					
Pereira, Cossi and Mantovani (2013)	Deterministic	×	×	✓	✓	✓	×	✓	×	×	×
Tabares et al. (2016)	Deterministic	✓	×	✓	×	✓	×	✓	✓	×	×
Xie et al. (2018)	Scenario-based stochastic	✓	✓	✓	×	×	✓	×	✓	×	×
Arias et al. (2018)	Chance constraint	✓	×	✓	✓	×	×	×	✓	×	✓
Melgar-Dominguez, Pourakbari-Kasmaei and Mantovani (2019)	Two-stage Robust	×	×	✓	✓	✓	×	✓	✓	✓	✓
Home-Ortiz et al. (2020)	Scenario-based stochastic	✓	×	✓	×	×	×	×	✓	✓	✓
Ehsan and Yang (2020a) Ehsan e Yang (2020b)	Scenario-based stochastic	✓	×	✓	✓	×	×	×	✓	×	✓
Lima et al. (2022)	Scenario-based stochastic	✓	×	✓	×	×	×	×	✓	✓	×
Mejia et al. (2022)	Scenario-based stochastic	×	×	✓	✓	×	×	✓	✓	✓	×
This work	Scenario-based stochastic	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

✓: considered, ×: not considered

Source: Elaborated by the author.

In Chapter 4, the proposed solution technique is described. The mathematical justification is presented first and then the proposed methodology is described in detail.

In Chapter 5, the case studies are presented and numerical results are analyzed and discussed. Also, key information about planning data is presented and the planning reliability is addressed and measured.

Finally, in Chapter 6, the conclusions are drawn and related future works are suggested.

6 CONCLUSIONS AND FUTURE WORKS

In this work, a multistage planning model for active distribution systems under uncertainty has been proposed. In order to handle the uncertainties a scenario-based two-stage stochastic approach has been used. Unlike the traditional models based on two-stage stochastic programming, the proposed model has modeled and used the uncertainties associated with the operating parameters in order to get more realistic and reliable representative operating scenarios (ROSs). Thus, the uncertainties from conventional demand, EVs, prosumers, and renewable energy resources have been addressed.

6.1 CONCLUSIONS

The results show that considering the operating uncertainties leads to more robust investment plans than the traditional approach where just the expected forecast values are considered. Additionally, this work has implemented a novel robust k-means method to obtain robust ROSs that leads to more robust investment plans compared with those obtained using the traditional K-means. In general, it has been shown that the planning robustness, under a scenario-based two-stage stochastic approach, can be increased through the proper selection of ROSs.

Also, for the sake of applicability in the industry, important realistic aspects about planning and operation of distribution systems have been considered in this work, as the elapsed life of the existing assets and substation transformer losses. It has been shown that considering the elapsed life of the existing assets modifies the replacement times and the selection of the conductors. Also, its use leads to realistic information about the investments values, which is important for DISCO's accounting.

Additionally, the work has presented the most complete portfolio of planning actions so far in order to obtain the best planning configuration and to draw conclusions about the interaction of the different devices involved in the system operation. Thus, it has been concluded that the joint operation of fixed CBs, switchable CBs and SVCs performs better than the individual operation of that devices.

The results show a high performance of the proposed model and solution technique, obtaining high-quality and feasible solutions for the planning problem in relative short times. Feasibility has been guaranteed regarding the original non-convex MINLP problem. CO_2 emission reduction goals have been met, mainly, through the installation of PV, wind and EES systems.

Finally, a post-planning stage to address and measure the planning reliability in terms of substation and conductor overload as well as voltage limits violation has been implemented. It has been shown that this stage is important and necessary when using a scenario-based two-stage stochastic approach, since a priory it can not be known how the system will react to unexpected scenarios from uncertainty realizations.

6.2 FUTURE WORKS

Future works can consider the following topics:

1. The analysis and exploitation of the flexibility at the transmission/distribution interface considering the increasing penetration of prosumers and distributed independent producers.
2. The implementation of robust and chance-constraint models for the planning of active distribution systems and the analysis of pros and cos of each uncertainty approach (stochastic, robust and chance constraint).
3. The adequacy and specialization of the proposed solution technique for general OPF problems considering different problem sizes (with focus on large-scale problems).
4. The developing of a planning model that minimizes the distribution system costs while maximizing the profit of distributed independent producers.

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