UNIVERSIDADE ESTADUAL PAULISTA
"JÚLIO DE MESQUITA FILHO"
FACULDADE DE ENGENHARIA
CÂMPUS DE ILHA SOLTEIRA

MARIA NATALY BAÑOL ARIAS

INTEGRAÇÃO DE VEÍCULOS ELÉTRICOS NO PLANEJAMENTO DA EXPANSÃO DOS SISTEMAS DE DISTRIBUIÇÃO

Ilha Solteira

2019

Maria Nataly Bañol Arias

INTEGRAÇÃO DE VEÍCULOS ELÉTRICOS NO PLANEJAMENTO DA EXPANSÃO DOS SISTEMAS DE DISTRIBUIÇÃO

Tese de Doutorado submetida ao Programa de Pós-Graduação em Engenharia Elétrica da Faculdade de Engenharia - Câmpus Ilha Solteira, UNESP, como parte dos requisitos para a obtenção do título de Doutora em Engenharia Elétrica.
Especialidade: Automação.

Prof. Dr. John Fredy Franco Baquero
Orientador

Ilha Solteira

2019

FICHA CATALOGRÁFICA
Desenvolvido pelo Serviço Técnico de Biblioteca e Documentação

B221i

Bañol Arias, Maria Nataly.
Integração de veículos elétricos no planejamento da expansão dos sistemas de distribuição / Maria Nataly Bañol Arias. -- Ilha Solteira: [s.n.], 2019
172 f. : il.

Tese (doutorado) - Universidade Estadual Paulista. Faculdade de Engenharia de Ilha Solteira. Área de conhecimento: Automação, 2019

Orientador: John Fredy Franco Baquero
Inclui bibliografia

1. Incertezas. 2. Planejamento da expansão. 3. Programação linear inteira-mista. 4. Restrições probabilísticas. 5. Sistemas de distribuição de energia elétrica. 6. Veículos elétricos.

Raiane da Silva Santos
Raiane da Silva Santos
Supervisora Técnica de Seção
Seção Técnica de Referência, Atendimento ao usuário e Documentação
Diretoria Técnica de Biblioteca e Documentação
CRB/8 - 9999

unesp

UNIVERSIDADE ESTADUAL PAULISTA

Câmpus de Ilha Solteira

CERTIFICADO DE APROVAÇÃO

TÍTULO DA TESE: Integração de veículos elétricos no planejamento da expansão dos sistemas de distribuição

AUTORA: MARIA NATALY BAÑOL ARIAS
ORIENTADOR: JOHN FREDY FRANCO BAQUERO

Aprovada como parte das exigências para obtenção do Título de Doutora em ENGENHARIA ELÉTRICA, área: Automação pela Comissão Examinadora:

Prof. Dr. JOHN FREDY FRANCO BAQUERO
Departamento de Engenharia Elétrica / Universidade Estadual Paulista Júlio de Mesquita Filho, Câmpus Experimental Rosana

Prof. Dr. RUBEN AUGUSTO ROMERO LAZARO
Departamento de Engenharia Elétrica / Faculdade de Engenharia de Ilha Solteira

Dr. JONATAS BOAS LEITE
Departamento de Engenharia Elétrica / Faculdade de Engenharia de Ilha Solteira

Prof. Dr. EDUARDO NOBUHIRO ASADA
Departamento de Engenharia Elétrica e de Computação / Escola de Engenharia de São Carlos - USP

Profa. Dra. FERNANDA CASEÑO LIMA TRINDADE ARIOLI
Departamento de Sistemas e Energia / Universidade Estadual de Campinas - UNICAMP

Ilha Solteira, 15 de fevereiro de 2019

Dedico este trabalho à minha família, minha força, meu sorriso, os principais motivos da minha existência.

AGRADECIMENTOS

Agradeço primeiramente a Deus pelo dom da minha vida e pela oportunidade de fazer realidade todos meus sonhos.

Agradeço aos meus Pais Orlando e Luciela pelo apoio incansável, pelas infinitas mostras de carinho, pelos conselhos e a educação que me brindaram sempre. Pelos valores que me inculcaram desde criança e que me tornaram a mulher que hoje eu sou. Aos meus irmãos Daniel e Daniela pela força e a alegria transmitida em todo momento. Por sempre me acompanhar e me animar nos momentos mais difíceis. A minha família, meus avós, ti@s e prim@s, e especialmente a minha avó Blanca e minha tia Marta pelas orações e pelas palavras de sabedoria.

Ao Professor Fredy, pela excelente orientação, pelas ideias, o compromisso, a dedicação e a paciência durante o desenvolvimento do meu mestrado e o doutorado. Sem ele não teria sido possível finalizar este trabalho com sucesso.

Ao Professor Rubén pela oportunidade de vir para Ilha Solteira. Pelos sábios conselhos e pela amizade e apoio durante meu passo por esta cidade.

Ao Juan, pela companhia, força, paciência e carinho em todo momento. Obrigada por compartilhar seus conhecimentos comigo e por me fazer parte da sua vida.

A minha família escolhida por Deus nesta cidade, Aleja, Gio, Nata e Nico. Obrigada pela companhia, pelos ensinos, conselhos, apoio e carinho em todo momento. Pela alegria infinita que sempre me transmitiram e pela força nos momentos difíceis. Vocês fizeram minha vida mais fácil neste lugar do mundo.

Aos meus amigos Ozy Daniel e Carlos, minha turminha do café. Obrigada pela ajuda infinita durante esta longa jornada. Pela compreensão, paciência, carinho e amizade. Vocês alegraram meu dia a dia com suas histórias, jogos, brincadeiras e dramas e sempre conseguiram colocar um sorriso na minha cara sem importar a situação.

Aos meus amigos da igreja, umas pessoas maravilhosas que me acolheram com muito carinho e me brindaram uma amizade verdadeira. Vocês se tornaram minha família na fé e no amor de Deus.

A cada um dos meus amigos em Colômbia, que sempre me enviaram mensagens de apoio e força e que me acompanharam durante este processo até o final.

Ao Professor Chresten Træholt por me acolher no grupo de pesquisa: *Distributed Energy Resources* e ao Seyed H. pela grande colaboração durante meu estágio de doutorado sanduíche na *Tecnhical University of Denmark*.

Ao LAPSEE, a UNESP, e ao Programa de Pós-Graduação em Engenharia Elétrica da FEIS, pela infraestrutura oferecida para o desenvolvimento deste trabalho.

Aos apoios financeiros fornecidos pela Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Código de Financiamento 001 e pela Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP), projeto 2015/21972-6.

There is nothing permanent except change.

Heraclitus

RESUMO

A crescente penetração dos Veículos Elétricos (VEs) no setor de transportes representa um novo e grande desafio para o planejamento da expansão e da operação dos Sistemas de Distribuição de Energia Elétrica (SDEEs) devido ao correspondente aumento da demanda associada ao carregamento das baterias. Portanto, devem ser desenvolvidos métodos que ajudem os SDEEs a lidar com esses desafios, considerando as incertezas associadas às demandas convencionais e aos VEs. Nesta tese é proposto um método robusto baseado em um modelo de Programação Linear Inteira-Mista (PLIM) para auxiliar a integração de VEs no SDEE. O método proposto permite resolver o problema de planejamento multi-estágio da expansão do SDEE considerando a alocação e o dimensionamento de Estações de Carregamento de VEs (ECVEs). Restrições probabilísticas são usadas na formulação proposta para lidar com as incertezas associadas à demanda, garantindo o cumprimento da capacidade de potência das subestações com um nível de confiança especificado. O modelo proposto para o planejamento da expansão avalia a construção e/ou reforço de subestações, ECVEs e circuitos, assim como também a alocação de unidades de geração distribuída e bancos de capacitores ao longo do horizonte de planejamento. O modelo de PLIM proposto é resolvido através de técnicas de otimização clássica visando garantir a solução ótima do problema. A eficiência e robustez do modelo são verificadas usando sistemas teste de 18 e 54 nós, junto com simulações de Monte Carlo para verificar o cumprimento da restrição probabilística proposta. Os resultados obtidos indicam que o método proposto é uma ferramenta eficiente que pode ser aplicada no planejamento da expansão de futuros SDEEs com alta penetração de VEs.

Palavras-chaves: Incertezas. Planejamento da expansão. Programação linear inteira-mista. Restrições probabilísticas. Sistemas de distribuição de energia elétrica. Veículos elétricos.

ABSTRACT

The increasing penetration of electric vehicles (EVs) in the transportation sector represents a new challenge for the expansion planning of electrical distribution systems (EDS) due to the corresponding increase of the energy demand. Therefore, methods to support the EDS considering the uncertainties associated with conventional and EV demands should be developed. This thesis presents a methodology to consider the EV integration into the EDS. A mixed-integer linear programming (MILP) model is proposed to solve the multi-stage expansion planning of EDS considering the allocation and sizing of EV charging stations (EVCSs). Chance constraints are used in the formulation to deal with the uncertainties associated with the demands, guaranteeing the fulfilment of the substation capacities within a given confidence level. The proposed model for the expansion planning considers the construction/reinforce of substations, EVCSs and circuits as well as the allocation of distributed generation units and capacitor banks along the planning horizon. The proposed MILP model guarantees optimality using classical optimization techniques. The efficiency and robustness of the model is verified using two test systems with 18-nodes and 54-nodes. Monte Carlo simulations were carried out to verify the compliance of the proposed chance constraint.

Key-words: Chance constraints. Electrical distribution systems. Electric vehicles. Expansion planning. Mixed-integer linear programming. Uncertainties.

LISTA DE ILUSTRAÇÕES

LISTA DE TABELAS

LISTA DE ABREVIATURAS E SIGLAS

BC	Banco de Capacitores
BEVs	*Battery Electric Vehicles*
CA	Corrente Alternada
CC	Corrente Contínua
ECVEs	Estações de carga de Veículos Elétricos
EPRI	*Electric Power Research Institute*
FC	*Fast Charger*
GD	Geração Distribuída
HEV	*Hybrid Electric Vehicles*
IEA	*International Energy Agency*
IEC	*International Electrotechnical Commission*
Li-Íon	Íons de lítio
NiMH	Hidreto metálico de níquel
OSD	Operador do Sistema de Distribuição
PCSOIM	Programação Cônica de Segunda Ordem Inteira Mista
PESD	Planejamento da Expansão dos Sistemas de Distribuição
PESDE	Planejamento da Expansão dos Sistemas de Distribuição Estático
PESDM	Planejamento Multi-estágio da Expansão dos Sistemas de Distribuição
PHEVs	*Plug-in Hybrid Electric Vehicles*
PLIM	Programação Linear Inteira Mista
PL	*Parking Lot*
PNLIM	Programação Não Linear Inteira Mista

RP	Restrição Probabilística
RT	Regulador de Tensão
SAE	*Society of Automotive Engineers*
SC	*Slow Charger*
SDEE	Sistema de Distribuição de Energia Elétrica
SMC	Simulações de Monte Carlo
SOC	*State of Charge*
V2G	*Vehicle to Grid*
VEs	Veículos Elétricos

TRABALHOS PUBLICADOS PELA AUTORA

Revistas Internacionais

1. M. N. Bañol; A. Tabares; J. F. Franco; M. Lavorato; R. Romero. Robust Joint Expansion Planning of Electrical Distribution Systems and EV Charging Stations. *IEEE Transactions on Sustainable Energy*, vol. 9, no. 2, pp. 884-894, April 2018.

2. M. N. Bañol; M. Lavorato; J.F. Franco; R. Romero. Metaheuristic optimization algorithm for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation. *Electric Power Systems Research*, vol. 142, pp. 351-361, January 2017.

3. M. N. Bañol; S. Hashemi; P.B. Andersen; C. Træholt; R. Romero. Distribution System Services Provided by Electric Vehicles: Recent Status, Challenges, and Future Prospects. *IEEE Transactions on Intelligent Transportation Systems*, to be published.

4. M. N. Bañol; S. Hashemi; P.B. Andersen; C. Træholt; R. Romero. Assessment of Economic Benefits for EV Owners Participating in the Primary Frequency Regulation Markets. *IEEE Transactions on Transportation Electrification*, under review.

Congressos Internacionais

1. M. N. Bañol; S. Hashemi; P.B. Andersen; C. Træholt; R. Romero. V2G Enabled EVs Providing Frequency Containment Reserves: Field Results. *Proceedings of the 19th IEEE International Conference on Industrial Technology (IEEE ICIT 2018)*, 2018. p. 1-6, Lyon.

2. M. N. Bañol; R. Romero; J.C. López; M. Rider. Optimal Sizing of Stationary Energy Storage Systems Participating in Primary Frequency Regulation Markets. *Proceedings of the 2016 IEEE PES Transmission & Distribution Conference and Exposition (T&D-LA 2018)*, 2018. p. 1-6, Lima.

3. M. N. Bañol; J. F. Franco; M. Lavorato; R. Romero. GRASP Algorithm for Charging Coordination of Plug-In Electric Vehicle in Electrical Distribution Systems. *Proceedings of the 2016 IEEE PES Transmission & Distribution Conference and Exposition (T&D-LA 2016)*, 2016. p. 1-6, Morelia.

4. M Gjelaj; NB Arias; C Træholt; S. Hashemi. Multifunctional Applications of Batteries within Fast-Charging Stations based on EV Demand-Prediction of the

Users' Behaviour. *Proceedings of the 2018 7th International Conference on Renewable Power Generation (RPG 2018)*, 2018, p. 1-7, Copenhagen.

5. S. Hashemi; NB Arias; P.B. Andersen; B. Christensen; C Træholt. Frequency Regulation Provision Using Cross-Brand Bidirectional V2G-Enabled Electric Vehicles. *Proceedings of the 2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE 2018)*, 2018, p. 249-254, Oshawa.

Congressos Nacionais

1. M. N. Bañol; A. Tabares; M. Lavorato; C. Torezzan. Um Modelo de Programação Linear Estocástico para o Problema de Planejamento da Expansão dos Sistemas de Distribuição de Energia Elétrica*. In: XLVIII Simpósio Brasileiro de Pesquisa Operacional – SBPO, 2016*, Vitória. Anais do XLVIII Simpósio Brasileiro de Pesquisa Operacional, 2016. Vitória.

SUMÁRIO

1 INTRODUÇÃO

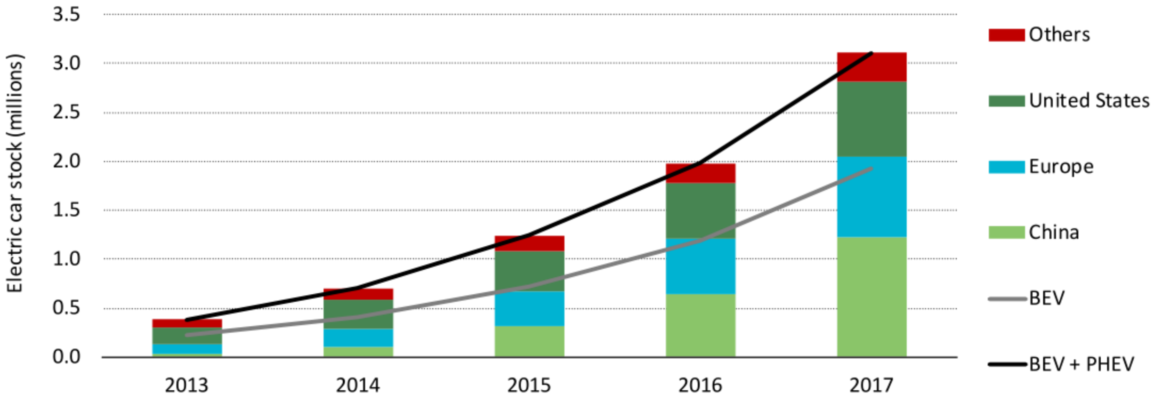
1.1 ANTECEDENTES E MOTIVAÇÃO

Os sistemas elétricos encontram-se em constante evolução devido à progressiva integração de novas tecnologias desenvolvidas para enfrentar desafios políticos, institucionais, sociais, assim como também ambientais. Em termos dos desafios ambientais, por exemplo, a mudança climática apresenta uma crescente preocupação global, dando passo à criação de medidas políticas de proteção ambiental (BULKELEY; PATERSON; STRIPPLE, 2016). Com isso, a redução da emissão de gases de efeito estufa (principal causa da mudança climática) faz parte do conjunto de políticas globais que visam o cuidado do meio ambiente e tem-se estabelecido como um dos principais objetivos de países europeus e americanos como Alemanha, Itália, França e Inglaterra, Canadá, Estados Unidos e mesmo Brasil.

Em consequência, as fontes de produção de energia renovável vêm sendo integradas progressivamente nos sistemas elétricos como principal opção para atingir o objetivo de redução de emissões. Além disso, a redução de custo e o aumento de eficiência de tecnologias tais como os veículos elétricos (VEs) e os dispositivos de armazenamento de energia permitem o melhor aproveitamento de energias limpas. Assim, espera-se nos próximos anos um incremento no uso de VEs no setor de mobilidade, dado que, além de incentivar o uso de energia renovável não contaminante, também diminuem a alta dependência de combustíveis fósseis (CCC, 2013). Ainda, os VEs representam uma opção econômica para os usuários pelos menores custos de operação e manutenção, quando comparados com os custos de veículos tradicionais a gasolina (CARLEY et al., 2013).

Segundo o estudo realizado pela *International Energy Agency* (IEA), as vendas de VEs aumentaram 54% entre o ano 2016 e 2017, com mais de um milhão de VEs vendidos no mundo inteiro durante o ano 2017. Ao final do mesmo ano, aproximadamente 3 milhões de VEs encontravam-se circulando pelas ruas, 57% mais do que o estimado no ano 2016 (INTERNATIONAL ENERGY AGENCY, 2018a). Na Figura 1 é possível observar o crescimento do uso de VEs nos últimos anos em alguns países do mundo; pode-se conferir também que a curva de penetração apresenta uma tendência crescente. Além disso,

Figura 1 – Crescimento do uso de VEs (2013-2017)

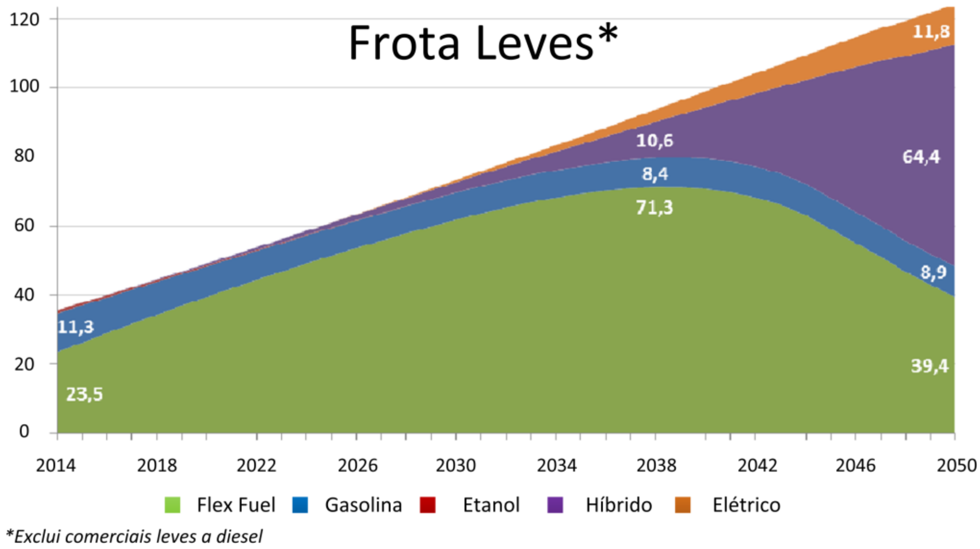


Fonte: Agência International de Energia (INTERNATIONAL ENERGY AGENCY, 2018b)

estima-se uma penetração de 190 milhões de VEs em 2035 e 320 milhões em 2040 no mundo inteiro (BP, 2018).

No Brasil, têm-se adotado políticas urbanas e ambientais focadas na diminuição do consumo de combustíveis líquidos e na consequente redução das emissões de gases de efeito estufa (10,1% até o fim de 2028 (LINDNER et al., 2018)), visando essencialmente dois objetivos: incentivar investimentos em transportes massivos e definir os ritmos de incorporação das tecnologias mais avançados nos veículos leves e pesados. No contexto do mercado brasileiro, os VEs ainda estão longe de ser usados como principal meio de transporte devido ao alto custo das baterias (o qual representa um terço do custo total do VE), à falta de infraestrutura de carregamento e ao alto investimento inicial. No entanto, de acordo com estudos realizados pela Empresa de Pesquisa Energética, a frota brasileira de VEs licenciados em 2017 era de aproximadamente 3600 entre VEs e híbridos, e estima-se uma penetração de 360000 VEs em 2026 (COELHO, 2017). Estima-se também que a frota nacional de veículos leves e elétricos deverá atingir 125 milhões de unidades em 2050. Os veículos híbridos representarão 52% desta frota, correspondendo a um total de 64,4 milhões de unidades e os VEs representarão 9%, totalizando 11,8 milhões de unidades (EMPRESA DE PESQUISA ENERGÉTICA - EPE, 2016), conforme ilustra a Figura 2.

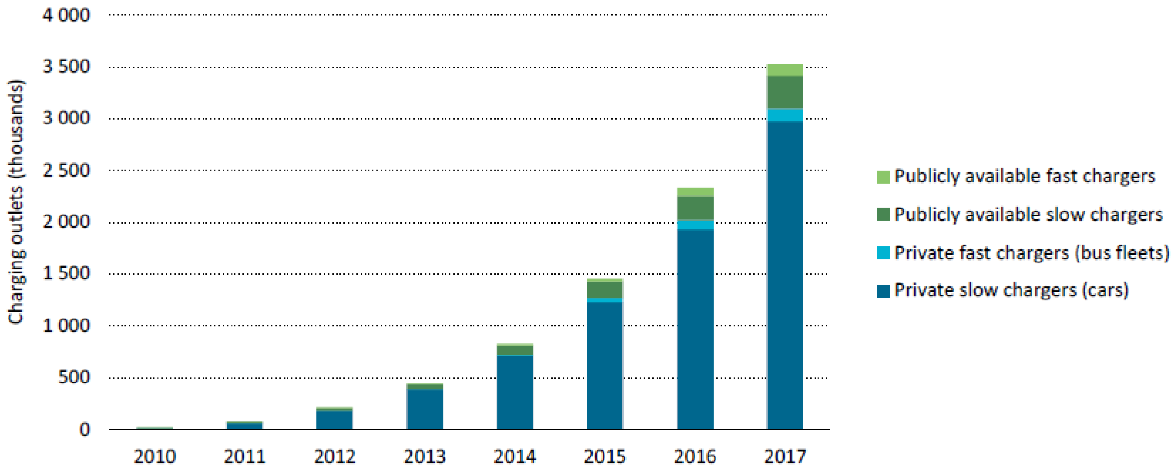
Figura 2 – Previsão do crescimento do uso de VEs no Brasil



Fonte: Empresa de Pesquisa Energética (EMPRESA DE PESQUISA ENERGÉTICA - EPE, 2016)

Considerando o crescimento acelerado da penetração de VEs no mundo inteiro, é clara a necessidade de proporcionar uma infraestrutura de carregamento adequada, que permita satisfazer os requerimentos de energia por parte dos usuários proprietários de VEs, que proporcione segurança para os usuários na hora de adquirir um VE e que, além disso, incentive ainda mais o uso dos mesmos (QUEROL, 2016; WANG et al., 2013). A Figura 3 mostra a tendência contínua de aumento da instalação de carregadores de diferentes tipos a nível mundial, o que confirma sua integração nas redes de distribuição. Nesse contexto, a carga associada aos VEs resultará em um incremento da demanda de energia elétrica que, de acordo com o lugar de carregamento, apresenta características diferentes (GODINA et al., 2016). Os VEs podem ser carregados em zonas residenciais (causando um incremento distribuído da demanda) ou em estações de carregamento público (ECVEs) também conhecidas como *Parking Lots* (PLs) ou eletropostos (levando a um incremento da demanda concentrado em alguns pontos específicos da rede). No caso das estações de carregamento público, existe ainda a necessidade de determinar qual seria o melhor ponto para sua alocação, a quantidade de carregadores que devem ser instalados em cada ponto e de que tipo, já que essas decisões dependem de diversos fatores tais como as condições atuais da rede elétrica, os níveis de cobertura, entre outros (LIU; WEN; LEDWICH, 2013; NICHOLAS; HALL, 2018; ZHANG et al., 2016).

Figura 3 – Crescimento da instalação de infraestrutura de carga de VEs



Fonte: Agência International de Energia (INTERNATIONAL ENERGY AGENCY, 2018b)

Em ambos os casos, o incremento da demanda convencional associado à carga dos VEs pode provocar impactos prejudiciais para os sistemas de distribuição de energia elétrica (SDEEs) dado que o consumo de potência de um VE em algumas horas do dia pode ser mais que o dobro do consumo de potência de uma residencia no mesmo horário (QUIRÓS-TORTÓS et al., 2016). Alguns trabalhos têm demonstrado os impactos negativos da integração de VEs nos SDEEs. Problemas na operação da rede tais como a elevação dos picos de carga, operação fora dos limites técnicos aceitáveis, incremento das perdas de energia, além do risco de piorar a qualidade do serviço e incorrer em penalidades impostas pelas entidades reguladoras, são alguns dos problemas identificados na literatura (LOPES; SOARES; ALMEIDA, 2011), (DUBEY; SANTOSO, 2015; VELDMAN; VERZIJLBERGH, 2015; XIONG et al., 2015). Por outro lado, alguns países com uma alta penetração de VEs já têm enfrentado problemas na operação da rede, como é o caso da Noruega, onde o número de VEs é tão grande que as redes de distribuição não conseguem satisfazer os níveis de demanda (BERGGREEN, 2017). Assim, é claro que os operadores do sistema de distribuição (OSDs) devem-se preparar para lidar com uma penetração a grande escala de VEs que provocará grandes mudanças nas suas redes.

Existem diversas formas de mitigar os problemas resultantes da integração dos VEs nas redes de distribuição. Uma opção está relacionada com a adaptação ou reforço do SDEE. A rede de distribuição deve ser expandida devido ao crescimento futuro da demanda, já que a rede existente pode não estar adequadamente dimensionada para atender demandas adicionais e fornecer o serviço com os mesmos padrões de qualidade. Nesse contexto, o planejamento da expansão do SDEE deve ser feito considerando o incremento da demanda associada à carga dos VEs, tanto no caso de carregamento residencial, como no caso de carregamento público, sendo que neste último, a alocação e o dimensionamento das ECVEs deveriam ser contemplados dentro do plano de expansão, como sugerido por Zheng et al., (2014) e Yao et al., (2014).

Outros trabalhos sugerem a criação de estratégias de coordenação de carga ou descarga dos VEs fazendo uso da sua natureza flexível, visando evitar reforços onerosos da rede, assim como minimizar as perdas de energia, além de melhorar a operação do SDEE. Nesse contexto, a integração dos VEs nas redes de distribuição seria enfrentada através do planejamento da operação do SDEE, incluindo estratégias inteligentes para a coordenação de dispositivos controláveis tais como geradores distribuídos, bancos de capacitores, reguladores de tensão, fontes de armazenamento de energia e inclusive, o gerenciamento da carga e/ou descarga das baterias dos VEs (LACEY; PUTRUS; BENTLEY, 2017; QUIRÓS-TORTÓS et al., 2016; VELDMAN; VERZIJLBERGH, 2015).

Assim, a penetração a grande escala de VEs nos SDEEs representa um novo desafio para as empresas de distribuição já que é necessário ter uma infraestrutura adequada com as características de carga estabelecidas para satisfazer os novos requisitos de energia dos usuários de VEs independentemente do lugar de carregamento. Portanto, os OSDs, os quais são responsáveis pela entrega eficiente e confiável de energia elétrica aos consumidores finais, devem se preparar para lidar com a crescente penetração de VEs e devem adaptar suas redes de distribuição para garantir um serviço de qualidade de acordo com os regulamentos estabelecidos.

Por outro lado, em vista de que os parâmetros associados ao crescimento da demanda são de natureza incerta, é importante considerar a estocasticidade associada às demandas tanto convencionais como dos VEs no planejamento da expansão e operação do SDEE (LIU; WEN; LEDWICH, 2011; NEYESTANI et al., 2015). Vários trabalhos têm demonstrado que as incertezas podem afetar drasticamente o desempenho de um sistema e que as soluções obtidas sob os cenários determinísticos podem se tornar infactíveis quando as incertezas nos parâmetros ou variáveis do sistema são consideradas

(SCHUËLLER; JENSEN, 2008). No caso do planejamento da expansão do SDEE, se as incertezas não são incluidas no processo, pode acontecer que as redes não estejam suficientemente dimensionadas para atender a demanda, arriscando a qualidade do serviço e provocando multas para as concessionárias. Assim, as incertezas devem ser devidamente levadas em conta durante o planejamento, a fim de obter planos de expansão mais eficientes, confiáveis e melhores adaptados às condições reais dos SDEEs.

Motivado pelos fatos anteriores, nesta tese, pretende-se estudar o impacto da integração a grande escala de VEs em redes de distribuição de acordo com o ponto de conexão dos VEs e se propõe um método que permita considerar a demanda associada aos VEs dentro do planejamento da expansão dos sistemas de distribuição levando em consideração as incertezas associadas tanto ao crescimento da demanda convencional como da penetração dos VEs.

1.2 OBJETIVOS E CONTRIBUIÇÕES DO TRABALHO

1.2.1 Objetivos do trabalho

Esta tese lida com a integração a grande escala dos VEs no planejamento da expansão do SDEE, em particular com as dificuldades que podem aparecer na hora de representar a demanda associada aos VEs. O trabalho se concentra em um método para o planejamento conjunto das redes de distribuição e ECVEs e investiga o impacto do lugar de conexão dos VEs, tendo em conta a natureza incerta das demandas convencionais e dos VEs. Assim, o objetivo principal deste trabalho é desenvolver modelos matemáticos que permitam a integração em grande escala de VEs no planejamento da expansão do SDEE. O trabalho é desenvolvido conforme os seguintes aspectos:

1. Modelagem do problema de planejamento multi-estágio da expansão dos SDEEs (PESDM) considerando a incorporação de unidades de geração distribuída (GD), bancos de capacitores (BCs) e ECVEs;
2. Representação do carregamento dos VEs em zonas residenciais e representação da operação das ECVEs dentro do problema de PESDM;
3. Modelagem robusta do problema de planejamento conjunto da expansão do SDEE multi-estágio e as ECVEs considerando as incertezas associadas à demanda convencional e dos VEs através de restrições probabilísticas;

4. Análise do impacto da integração dos VEs nos sistemas de distribuição considerando o lugar de conexão dos VEs e análise da importância de considerar as incertezas associadas às demandas na expansão da rede.

1.2.2 Contribuições do trabalho

As principais contribuições deste trabalho são:

- Um modelo de PLIM para resolver o problema de planejamento multi-estágio da expansão dos SDEEs considerando ações tradicionais de planejamento, alocação e operação de unidades de GD e BCs, e alocação e dimensionamento de ECVEs;
- Uma metodologia e modelagem matemática para representar a demanda associada aos VEs dentro do PESDM de acordo com o seu lugar de conexão;
- Um modelo de programação robusta baseado em restrições probabilísticas o qual é adequado para considerar o comportamento estocástico das demandas convencionais e dos VEs no problema de PESDM, visando satisfazer os limites de operação do sistema;
- Uma nova análise da integração dos VEs nos SDEEs que examina o impacto da demanda dos VEs no PESDM de acordo com o lugar de conexão e demonstra a importância de considerar as incertezas associadas à demanda dentro do PESDM.

1.3 ESTRUTURA DO TRABALHO

Esta tese está composta por seis capítulos, incluindo a introdução e cinco apêndices descritos como segue:

O Capítulo 2 apresenta uma revisão bibliográfica das metodologias propostas para resolver o problema de planejamento da expansão do SDEE considerando a alocação e dimensionamento de ECVEs, considerando os trabalhos mais relevantes desde o ano 2007 aproximadamente. Adicionalmente, é feita uma contextualização das principais tecnologias relacionadas com os VEs, as baterias, a infraestrutura e os padrões mundiais de carregamento.

No Capítulo 3, apresenta-se o problema de PESDM considerando a alocação e dimensionamento das ECVEs. É feita uma descrição geral do problema e apresentam-se as principais considerações para modelar as ECVEs. É discutido o modelo matemático proposto para resolver o problema de PESDM considerando a integração de VEs desde um enfoque determinístico.

No capítulo 4, apresenta-se um modelo robusto que permite levar em conta a natureza incerta da demanda convencional e dos VEs através da aplicação de restrições probabilísticas, desenvolvidas para definir a capacidade das subestações.

No capítulo 5, são analisados os resultados obtidos após a aplicação dos modelos propostos: determinístico e robusto. Os resultados apresentados são obtidos usando dois sistemas teste de 18 e 54 nós. O cumprimento das restrições probabilísticas é verificado através de simulações de Monte Carlo.

No Capítulo 6, são discutidas as principais conclusões da pesquisa e os trabalhos futuros.

Nos Apêndices A e B, são apresentados os dados dos sistemas de 18 e 54 nós respectivamente, utilizados para verificar a eficiência dos modelos propostos neste trabalho.

No Apêndice C, é apresentada a formulação da linearização por partes, enquanto no Apêndice D são apresentados os trabalhos relevantes publicados durante o andamento do doutorado.

Finalmente, no Apêndice E, é apresentado um resumo dos trabalhos desenvolvidos durante o doutorado sanduíche no exterior. Os métodos e os resultados principais associados a cada trabalho são apresentados através dos artigos preparados durante o estágio (publicados e/ou submetidos para avaliação e publicação). No apêndice B.1 são apresentados resultados reais associados à operação de uma frota de VEs que fornece serviços de regulação de frequência ao operador do sistema de transmissão na Dinamarca. No apêndice B.2 é apresentada uma revisão e classificação dos serviços que potencialmente podem ser fornecidos por VEs para operadores do sistema de distribuição e uma análise qualitativa de sua implementação em aplicações da vida real. Finalmente, no apêndice B.3 é apresentado uma análise do benefício económico que os proprietários dos VEs poderiam obter pela provisão de serviços de regulação de frequência.

2 REVISÃO BIBLIOGRÁFICA

Neste capítulo será apresentada uma breve revisão bibliográfica das diferentes metodologias propostas para modelar e resolver o problema clássico de planejamento da expansão do sistema de distribuição (PESD). Será incluída uma subseção introdutória correspondente aos conceitos básicos relacionados com os veículos elétricos e uma revisão bibliográfica das metodologias propostas para resolver o problema de PESD em conjunto com o planejamento das ECVEs. O estado da arte aqui apresentado é desenvolvido dando prioridade aos trabalhos propostos durante os últimos dez anos.

2.1 PLANEJAMENTO DA EXPANSÃO DOS SDEEs

O problema de PESD consiste em determinar o plano de expansão ótimo para o SDEE visando atender as demandas de energia futuras e respeitando as restrições operacionais do sistema (GÖNEN; RAMIREZ-ROSADO, 1986). O crescimento contínuo da demanda de energia elétrica obriga as empresas de distribuição de energia elétrica a expandirem seus sistemas a partir da aplicação de ações tradicionais de planejamento como são a construção e/ou reforço de subestações, assim como a construção e/ou recondutoramento dos circuitos necessários para suprir as demandas de energia de forma eficiente e confiável.

O PESD pode ser modelado como um problema de planejamento estático (PESDE), onde o planejamento é realizado com a previsão da demanda que existirá no final do horizonte de planejamento. Pode ser modelado também como um problema de planejamento multi-estágio (PESDM), onde o horizonte de planejamento é dividido em vários estágios, e as ações do planejamento são executadas nos diferentes estágios do horizonte de planejamento, sendo este último a melhor representação do comportamento real das redes elétricas (FLETCHER; STRUNZ, 2007).

Por outro lado, além das ações tradicionais de planejamento, o problema de PESD tem sido estendido considerando múltiplas alternativas de alocação e operação. Assim, entre essas alternativas encontram-se os Bancos de Capacitores (BCs), as unidades de Geração Distribuída (GD) e os Reguladores de Tensão (RTs), sendo que esses equipamentos contribuem com a redução dos custos operacionais do sistema (TABARES et al., 2016). Neste contexto, diversos modelos matemáticos têm sido propostos, onde os diferentes tipos de investimento que representam a construção, instalação e/ou alocação das diferentes ações de planejamento, com diferentes características cada um, são usualmente representados por variáveis binárias e/ou inteiras dentro do modelo matemático, elevando o custo computacional da solução. Encontram-se também as variáveis de operação associadas ao estado de operação do SDEE, as quais são representadas por variáveis contínuas. Assim, considerando as características do problema de PESD, este pode ser formulado como um problema de programação não linear inteiro-misto (PNLIM). Geralmente este tipo de problema é representado por modelos matemáticos de natureza combinatória e são conhecidos na literatura como problemas *NP-hard*.

Existem na literatura diferentes técnicas de solução, tais como algoritmos heurísticos, técnicas de otimização clássica que incluem programação linear, não linear, cônica, e programação inteira, assim como também metodologias de otimização baseadas em meta-heurísticas, propostas para resolver o problema de PESD.

Entre as metodologias de otimização clássica para resolver o problema de PESDM encontram-se os trabalhos apresentados por (HAFFNER et al., 2008a; HAFFNER et al., 2008b; LOTERO; CONTRERAS, 2011; TABARES et al., 2016) nos quais o problema é formulado como um problema de PLIM e resolvido através de algoritmos *branch and bound* e/ou *solvers* comerciais. Encontram-se também modelos de PNLIM do problema de PESDM que usam métodos de decomposição de *Benders* (FLETCHER; STRUNZ, 2007) e programação dinâmica (POPOVIĆ; POPOVIĆ, 2010; GANGULY; SAHOO; DAS, 2013), ou algoritmos *branch and bound* não lineares para resolver o problema de PESDE (LAVORATO, 2010).

Técnicas heurísticas e meta-heurísticas também têm sido bastante usadas para resolver o PESD. Algoritmos genéticos foram usados em (RAMIREZ-ROSADO; BERNAL-AGUSTIN, 1998; MARTINS; BORGES, 2011; MENDOZA et al., 2013; BAGHERI; MONSEF; LESANI, 2015), enquanto algoritmos de busca tabu foram aplicados em (RAMIREZ-ROSADO; DOMINGUEZ-NAVARRO, 2006; PARADA et al., 2010; COSSI et al., 2012), (PEREIRA JUNIOR et al., 2014; KOUTSOUKIS; GEORGILAKIS; HATZIARGYRIOU, 2014). Outros trabalhos resolvem o problema de PESD usando algoritmos de enxame de partículas (SEDGHI; ALIAKBAR-GOLKAR, 2013), *Simulated annealing* (POPOVIĆ; KERLETA; POPOVIĆ, 2014) e algoritmos imunes artificiais (SOUZA et al., 2011).

Por outro lado, diferentes metodologias têm sido desenvolvidas considerando as incertezas associadas a alguns parâmetros do problema de PESD. Assim, o crescimento da demanda, a potência gerada pelas fontes renováveis, os preços da energia, entre outros, são definidos como parâmetros estocásticos na maioria dos trabalhos que consideram incerteza na solução do problema de PESD. Entre as técnicas mais usadas para considerar incerteza no problema de PESD encontram-se as Simulações de Monte Carlo (SMC) (CARRANO et al., 2007; KOUTSOUKIS; GEORGILAKIS; HATZIARGYRIOU, 2014); a geração de cenários (MARTINS; BORGES, 2011) e a otimização avessa ao risco (SAMPER; VARGAS, 2013; BRUNO et al., 2016). Existem também modelos estocásticos de dois estágios (MONTOYA-BUENO; MUNOZ; CONTRERAS, 2015), e modelos robustos (FRANCO; RIDER; ROMERO, 2016; DEHGHAN; AMJADY; CONEJO, 2016) apresentados na literatura para considerar a incerteza no problema de PESD.

Os trabalhos de Georgilakis e Hatziargyriou (2015) e Tabares et al., (2016) apresentam um resumo detalhado das metodologias propostas para resolver o PESD. Assim, em seguida apresenta-se um resumo detalhado dos trabalhos mais relevantes usados para desenvolver o modelo aqui proposto.

O trabalho proposto em Lavorato (2010) resolve o problema de PESDE considerando como função objetivo a minimização dos custos de construção de subestações e circuitos, custos de operação e os custos de alocação de BCs e RTs. O modelo proposto leva em consideração as restrições que relacionam as leis de Kirchhoff, limites operacionais, controle de *taps* e restrições de radialidade. Foram desenvolvidas duas metodologias para resolver o problema: Um algoritmo heurístico construtivo especializado e um algoritmo *branch and bound* não linear.

Em Lavorato et al., (2012) os autores apresentam um modelo de PNLIM para o PESDE o qual é resolvido usando técnicas de otimização clássica. O trabalho foi focado principalmente na incorporação de restrições simples e eficientes para considerar a radialidade nos SDEEs e mostra as principais alterações que devem ser consideradas nos modelos para casos particulares do problema, como a presença de várias subestações, unidades de GD e nós de transferência de carga.

Em Franco, Rider e Romero (2014) é resolvido o problema de PESDE considerando a construção e/ou reforço de subestações e circuitos, alocação de BCs e a topologia radial do sistema. Os autores propõem um modelo de programação quadrático e convexo e usam *solvers* comercias de otimização para resolver o problema garantindo uma solução ótima.

No trabalho proposto em Munoz-Delgado, Contreras e Arroyo (2015) o problema de PESDM é resolvido considerando a construção e/ou reforço de subestações e circuitos, assim como também a instalação de diferentes alternativas de GD: convencional e eólica. O objetivo do modelo proposto é a minimização dos custos de investimento, operação, produção, perdas e energia não suprida, considerando como restrições os limites operacionais do sistema, limites de investimento e as condições de radialidade. O problema é formulado como um problema de PLIM e é resolvido via *solver* de otimização CPLEX, garantindo otimalidade na solução.

Os autores em Tabares et al., (2016) propõem um modelo de PNLIM para resolver o problema de PESDM, o qual é transformado em um modelo de PLIM através de técnicas de linearização. O modelo considera as ações tradicionais de planejamento como a construção e/ou reforço de subestações e circuitos em conjunto com a alocação e operação de BCs, unidades de GD e RTs, assim como também a reconfiguração do sistema. As restrições de radialidade e nós de transferência foram também considerados na formulação. O objetivo principal é minimizar os custos totais de investimento e operação do sistema durante o horizonte de planejamento, sendo que o modelo foi resolvido utilizando o *solver* comercial CPLEX visando obter a solução ótima do problema. Esse modelo foi usado como base para a realização do trabalho apresentado neste documento.

No trabalho apresentado em Franco, Rider e Romero, (2016) é proposto um modelo de programação cônica de segunda ordem inteira mista (PCSOIM) para resolver o problema de planejamento multi-estágio da expansão de subestações. A incerteza na demanda é considerada através de um modelo robusto que usa restrições probabilísticas garantindo que os limites na capacidade das subestações sejam satisfeitos com um dado nível de confiança. O modelo visa minimizar o custo total esperado do plano de expansão definido pelos custos fixos de investimentos, custos variáveis de operação e perdas de potência e pelo custo esperado da energia não suprida relacionado com um custo de penalização pela energia não suprida devido a falhas nas subestações e nos circuitos.

2.2 INTEGRAÇÃO DOS VEÍCULOS ELÉTRICOS NO PESDM

Neste trabalho, pretende-se estudar o impacto da alocação e dimensionamento de ECVEs como parte do problema de PESDM. Nesta subseção serão apresentados os conceitos básicos relacionados com os VEs e, posteriormente, serão apresentados os trabalhos mais relevantes que consideram as ECVEs dentro do problema de PESDM.

2.2.1 Veículos Elétricos

Os VEs existem desde finais do século XIX, sendo que o primeiro VE apareceu entre os anos 1834 e 1835. Um veículo elétrico é qualquer veículo que usa um motor elétrico para seu acionamento e que pode ser carregado desde uma fonte de eletricidade externa tal como uma tomada (SANDALOW, 2009). Existem vários tipos de VEs que podem ser classificados em veículos elétricos híbridos (*Hybrid Electric Vehicles - HEV*), veículos elétricos híbridos conectáveis (Plug-in Hybrid Electric Vehicles - PHEVs), e veículos elétricos a bateria (*Battery Electric Vehicles - BEVs).* Cada um dos VEs tem um sistema de carregamento das baterias diferente. Por exemplo, a bateria do HEV é carregada através do sistema de frenagem regenerativa e não possui conexão externa à rede. Já as baterias do PHEV e o BEV são carregadas diretamente desde a rede através de uma ECVE.

Como especificado no Capítulo 1, a penetração de VEs tem se acrescentado significativamente nos últimos anos. As principais motivações estão relacionadas com a redução da dependência aos combustíveis fósseis, redução das emissões, economia nos custos de energia e manutenção e suporte de energia em caso de faltas na rede de distribuição. Existe atualmente no mercado uma ampla gama de opções de VES, porém, entre os mais difundidos comercialmente encontram-se o Nissan *Leaf* com baterias de 24, 30 e 40 kWh (AUTOEVOLUTION, 2019; NISSAN, 2019), e o Tesla com baterias de 50, 75 e até 100 kWh (AUTOEVOLUTION, 2018).

2.2.2 Baterias

Os diferentes tipos de VEs presentes no mercado operam usando baterias recarregáveis com diferentes capacidades, as quais definem em parte a autonomia dos VEs. É esperado que quanto maior for a capacidade da bateria, maior será a autonomia do VE. No entanto, a bateria é um dos componentes mais caros (representa um terço do custo total do VE), tornando-se uma das principais barreiras para a adopção dos VEs.

A bateria é um dispositivo que permite o armazenamento de energia. Entre as principais tecnologias de baterias para VEs encontram-se as de hidreto metálico de níquel (NiMH), íons de lítio (Li-Íon), chumbo ácido e sódio-cloreto de níquel (Na/NiCl2), cada uma com diferentes vantagens, especialmente em relação ao tempo de duração (MAHMOUDZADEH ANDWARI et al., 2017).

A maioria dos VEs usam baterias de íons de lítio. Graças aos avanços tecnológicos nos últimos anos, tem sido observada uma redução nos custos das baterias e espera-se que os custos continuem diminuindo (BERCKMANS et al., 2017). Isso permitiria o uso de baterias de maior capacidade, resultando automaticamente em um aumento da autonomia dos VEs e melhorando o panorama para a adopção dos VEs como principal meio de transporte.

2.2.3 Infraestrutura de Carregamento: Normas e Padrões

Os VEs podem ser carregados através de uma tomada conectada à rede elétrica. O carregamento pode ser residencial ou comercial de acordo com as necessidades dos usuários, sendo necessária uma infraestrutura apropriada e devidamente planejada.

As técnicas de conexão disponíveis atualmente no mercado são a condutiva e a indutiva. Na conexão condutiva, a energia é transferida por meio de uma conexão direta entre o VE e o carregador usando um cabo, através de corrente alternada (CA) ou contínua (CC). Existe a conexão indutiva, conhecida também como conexão sem fio, no entanto, este tipo de conexão ainda se encontra em fase de desenvolvimento. A conexão condutiva esta normatizada pelo *Electric Power Research Institute* (EPRI) e é fisicamente apta para satisfazer os requisitos do consumidor e a indústria elétrica (BAÑOL ARIAS, 2015). Este tipo de conexão compõe-se de diferentes métodos que variam de acordo com a região. Os padrões mais conhecidos para o processo de carregamento de VEs são o norte-americano definido pela *International Electrotechnical Commission* (IEC), e que tipicamente define os modos de carregamento, e o padrão europeu definido pela *Society of Automotive Engineers* (SAE), quem define os níveis de carregamento. Existem outros padrões como o japonês CHAdeMO que define as normas para o carregamento rápido em CC.

Os modos de carregamento são definidos especificamente pelo padrão IEC 61851: *Electric Vehicle Conductive Charging System* (INTERNATIONAL ELECTROTECHNICAL COMMISSION (IEC) STANDARD, 2010), que basicamente descreve os requerimentos gerais e os protocolos de segurança e comunicação entre o VE, a ECVE e a rede (ver Tabela 1). Por outro lado, os níveis de carregamento especificamente são definidos pelo padrão SAE J1772: *Electric Vehicle and Plug-in Hybrid Electric Vehicle Conductive Charge Coupler* (SOCIETY OF AUTOMOTIVE ENGINEERS (SAE) STANDARD, 2010), que basicamente descreve os métodos de recarga condutiva para VEs através de CA e CC (ver Tabela 2). Vale a pena mencionar que esses padrões foram adotados e adaptados pela Associação Brasileira de Normas Técnicas (ABNT) para o carregamento dos VEs no Brasil.

Tabela 1 – Modos de carregamento definidos pela IEC 61851

Modo	Alimentação	Descrição	Fases	Corrente máxima [A]	Faixa de tensão [V]	Tempo aproximado de carga*
1	CA	Carga lenta. Carregamento residencial em uma tomada normal.	1	16	250	6-8 horas
			3	16	480	2-3 horas
2	CA	Carga lenta. Carregamento residencial em uma tomada normal com alguns equipamentos de proteção e segurança.	1	32	250	3-4 horas
			3	32	480	1-2 horas
3	CA	Carga lenta ou rápida usando uma tomada especial com capacidade de controle e proteção. Ideal para carregamento público, ECVEs.	1	32	250	3-4 horas
			3	250	690	8 – 10 minutos
4	CC	Carga rápida usando um carregador especial, ideal para carregamento público, ECVEs.		400	600	6 minutos

Fonte: (INTERNATIONAL ELECTROTECHNICAL COMMISSION (IEC) STANDARD, 2010)
* Tempo de carga para um VE Nissan *Leaf* com bateria de 24 kWh.

Os modos de carga 1 e 2 são mais generalizados na Europa e permitem um carregamento normal da bateria usando um módulo de carregamento localizado dentro do veículo; esses modos são muito simples, portanto, são o tipo de ligação preferencial para uso doméstico ou no local de trabalho. O modo de carga 3 apresenta restrições de

Tabela 2 – Níveis típicos de carregamento definidos pela SAE J1772

	CA			CC		
Nível	Potência [kW]	Tensão [V]	Corrente [A]	Potência [kW]	Tensão [V]	Corrente [A]
1	1,4	120	12	36	200-450	80
	1,9	120	16			
2	2,4	240	10	90	200-450	200
	3,8	240	16			
	7,7	240	32			
	19,2	240	80			
3	> 19,2	-	-	240	200-600	400

Fonte: Adaptado de (UN-NOOR et al., 2017)

infraestruturas não muito pesadas ou dispendiosas. Já o modo 4 é desenvolvido para carregar o VE a um alto nível de corrente de carga conseguindo carregar por exemplo, um VE com uma bateria de 100 kWh até um 80%, em aproximadamente 20 minutos, tornando-se a melhor opção para aplicações comerciais em postos de serviço similares aos postos de gasolina.

É importante mencionar que a potência de carga é o parâmetro com maior influência no impacto na rede. Assim, a demanda dos VEs é refletida no SDEE através do uso das estações de carregamento.

2.2.4 Planejamento integrado da expansão do SDEE e ECVEs

O problema de PESD tem sido amplamente estudado na literatura usando diferentes técnicas de solução. Porém, o PESD considerando a integração dos VEs ainda precisa ser explorado. Existem na literatura vários trabalhos que estudam a alocação e dimensionamento das ECVEs como um problema individual, no entanto, existem poucos trabalhos que consideram as ECVEs dentro do problema de PESD (HU; SONG, 2012; ZHENG et al., 2014; YAO et al., 2014; NEJADFARD-JAHROMI; RASHIDINEJAD; ABDOLLAHI, 2015; HUMAYD; BHATTACHARYA, 2017; MENESES DE QUEVEDO; MUNOZ-DELGADO; CONTRERAS, 2017; WANG et al., 2018; ZHANG et al., 2018). A seguir serão apresentados em detalhe os trabalhos que abordam o problema de PESD considerando a alocação e dimensionamento das ECVEs.

No trabalho apresentado em Hu e Song (2012) é proposto um modelo de PLIM para resolver o problema de PESDM levando em consideração a alocação e o dimensionamento de ECVEs. A função objetivo visa minimizar os custos totais de investimento e operação do SDEE, incluindo os custos de investimento associados às ECVEs. Considera-se dentro da formulação a construção e/ou reforço de subestações, circuitos e ECVEs e as restrições associadas aos limites de operação e radialidade. No entanto, os autores consideram a demanda associada aos VEs como uma carga adicional à demanda convencional desconsiderando as características associadas ao comportamento dos usuários de VEs.

Em Zheng et al., (2014) os autores propõem um algoritmo evolutivo para resolver o problema de alocação de ECVEs e estações de troca de baterias. A formulação proposta inclui as restrições operacionais do SDEE e a função objetivo consiste na maximização do benefício econômico, obtido da diferença entre os lucros obtidos pela venda de energia e os custos de reforço e adaptação (correspondentes aos custos de construção necessários para cobrir as deficiências do plano de expansão). Dado que a metodologia usada para resolver o problema é baseada em técnicas meta-heurísticas, a solução ótima do problema não é garantida.

Em Yao et al., (2014) os autores apresentam um modelo de planejamento conjunto do SDEE e ECVEs considerando as condições do tráfego. O problema é modelado como um problema multiobjetivo considerando a minimização dos custos de investimento e das perdas, e a maximização do serviço/uso das ECVEs rápidas e é resolvido através de um algoritmo evolucionário multiobjectivo. O comportamento estocástico dos usuários de VEs e os diferentes modos de carregamento são desconsiderados. Além disso, o modelo desconsidera o incremento anual da demanda e o impacto geográfico da localização das ECVEs. Assim, visando cobrir essas deficiências, os autores em Wang et al., (2018) apresentam um modelo estocástico multi-estágio para o planejamento integrado de redes de distribuição, ECVEs (rápidas e lentas) e estações de troca de baterias, incluindo restrições associadas à rede de transporte e fluxo do tráfego. O problema é modelado como um problema multiobjetivo considerando os mesmos objetivos propostos no trabalho anterior. O modelo considera as incertezas associadas à demanda dos VEs sob os diferentes modos de carregamento modeladas através de funções de distribuição de probabilidade para a hora de início, SOC inicial, e duração do tempo de carregamento. Técnicas meta-heurísticas são usadas para resolver o problema as quais têm a desvantagem de não garantir otimalidade na solução obtida. Por outro lado, a operação de unidades de GD e BCs é desconsiderada em ambos os trabalhos.

Em Nejadfard-JahromI, Rashidinejad e AbdollahI, (2015) é desenvolvido um modelo de otimização multi-objetivo considerando na função objetivo a minimização dos custos totais de investimento e operação ao mesmo tempo em que os indicadores de confiabilidade são maximizados. O problema é formulado como um PNLIM e é usado um algoritmo genético para resolvê-lo. A metodologia proposta é diferenciada de outras já que as ECVEs são modeladas como fontes de GD, as quais podem injetar potência à rede durante o horário de pico ou durante alguma contingência, ou extrair potência para carregar os VEs, através da tecnologia V2G. Nesse contexto, a alocação das ECVEs é influenciada pelos indicadores de confiabilidade associados ao sistema.

Os autores em Humayd e Bhattacharya (2017) propõem modelos de PNLIM para resolver o problema de PESDM considerando ações tradicionais de planejamento como a construção e/ou reforço de subestações e circuitos em conjunto com a alocação e operação de BCs e unidades de GD. Um aspecto interessante nesse trabalho é que os autores, além de considerar a demanda convencional, também incluem a demanda associada aos VEs sob as condições de carregamento controlado e não controlado e opções de resposta pelo lado da demanda. Os modelos foram resolvidos usando técnicas de otimização clássica usando os *solvers* COINBONMIN e SNOPT e foi analisado o impacto da integração dos VEs no plano de expansão do SDEE. Contudo, nesse trabalho desconsideram-se as incertezas associadas às demandas e a alocação e dimensionamento das ECVEs.

Em Meneses de Quevedo, Munoz-Delgado e Contreras (2017) os autores apresentam um modelo matemático baseado em programação estocástica para o problema de PESDM que considera além dos investimentos tradicionais, investimentos em fontes renováveis, baterias e ECVEs. As incertezas associadas às fontes renováveis e a demandas são tratadas através da geração de cenários. Uma das principais desvantagens da programação estocástica é que a complexidade do problema aumenta de acordo com o número de cenários usados. Além disso, este trabalho não considera diferentes tipos de VEs e ECVEs, o que pode ser não realista em cenários práticos.

Recentemente, em Zhang et al., (2018) os autores propõem um modelo de programação cónico de segunda ordem para o planejamento de ECVEs rápidas levando em consideração tanto as restrições da rede elétrica como a rede de transporte. O modelo define a alocação e o dimensionamento das ECVE modelando a operação das ECVEs em detalhe. O modelo considera a qualidade do serviço nas ECVEs, o fluxo do tráfego, a variação da demanda dos VEs no tempo. Em termos do problema de PESD, o modelo é estático e não considera a operação de unidades de GD nem de BCs.

A principal desvantagem da maioria das metodologias anteriormente expostas é a desconsideração das incertezas associadas às demandas tanto convencionais como dos VEs. A incerteza deveria ser considerada visando reduzir os riscos e evitar sub ou sobre investimentos que poderiam ocasionar problemas operacionais. Por outro lado, as metodologias acima descritas não consideram a alocação de unidades de GD nem BCs, as quais são alternativas que poderiam adiar reforços na rede, reduzindo os custos de investimento. Em relação às ECVEs, na maioria das metodologias é considerado somente um tipo de carregador e somente um tipo de VE é usado para representar a penetração dos VEs no sistema.

Nos próximos capítulos deste trabalho será apresentado um modelo para o problema de PESDM considerando alocação e dimensionamento de ECVEs, considerando diferentes modos de carregamento e diferentes tipos de VEs, em conjunto com um modelo robusto que permite representar a natureza incerta das demandas convencionais e dos VEs.

2.2.5 Planejamento das ECVEs

O problema de alocação e dimensionamento de ECVEs tem sido abordado de forma individual através de diversas técnicas de solução. Modelos de PLIM e PNLIM foram desenvolvidos em Liu, Wen e Ledwich, (2013) e Neyestani et al., (2015) respectivamente, enquanto técnicas meta-heurísticas tais como algoritmos genéticos (MORADIJOZ et al., 2013; Amini e Islam (2014) e enxame de partículas (LIU et al., 2012; PASHAJAVID; GOLKAR, 2013) foram usadas para resolver o problema. Estes trabalhos estão focados na solução do problema de planejamento das ECVEs sem considerar a expansão da rede. Os principais trabalhos usados como base para modelar as ECVEs no trabalho proposto neste documento são apresentados a seguir.

Em Liu, Wen e Ledwich, (2013) os autores propuseram uma metodologia de dois estágios para alocar e dimensionar ECVEs em conjunto com o PESD. No primeiro estágio são identificados os lugares ótimos para alocação da ECVE de acordo com alguns fatores ambientais, enquanto no segundo estágio é resolvido um modelo matemático de PNLIM para otimizar a alocação e o dimensionamento das mesmas. A função objetivo visa minimizar o valor líquido dos custos totais associados às ECVEs incluindo custos de investimento, operação, manutenção e perdas de energia durante o horizonte de planejamento. Foram incluídas as restrições do fluxo de potência, limites de tensão e corrente, e limites de potência reativa. As restrições associadas às ECVEs tais como capacidade máxima, potência mínima e máxima de carregamento, limites de carga máxima diária e limites do fator de potência de carga mínima foram representadas na modelagem. O processo de otimização foi resolvido através de um algoritmo modificado primal-dual de pontos interiores.

No trabalho apresentado em Neyestani et al., (2015) propõe-se um modelo de PLIM para representar o comportamento das ECVEs levando em consideração interações no mercado (mercados de reserva e venda de energia) e as restrições operacionais do sistema. A metodologia proposta para resolver o problema é dividida em dois estágios. No primeiro estágio maximiza-se o lucro obtido pela participação da ECVE no mercado de energia, considerando incertezas associadas ao comportamento dos usuários de VEs e ao preço da energia, junto com as restrições associadas à operação das ECVEs. No segundo estágio minimiza-se o custo de alocação das ECVEs desde o ponto de vista da ED considerando as incertezas associadas às fontes de geração renovável, em conjunto com as restrições operacionais do SDEE. Assim, nesse trabalho, o problema de alocação e dimensionamento de ECVEs é tratado como um problema de operação.

Em Mirzaei, Kazemi e Homaee (2015) os autores apresentam um enfoque probabilístico baseado no método de estimação de pontos para alocação e dimensionamento ótimo de ECVEs considerando a incerteza associada aos padrões de condução dos proprietários dos VEs. Os autores propõem uma metodologia de coordenação de carregamento de VEs visando calcular o benefício pelo intercâmbio de potência entre a ECVE e a rede (V2G). Nessa metodologia proposta, o objetivo principal é maximizar o lucro da ECVE. A função objetivo é composta pelos custos do terreno e instalação, manutenção, o lucro esperado pela injeção de potência na rede, e, o valor esperado da redução das perdas pela carga e descarga dos VEs em horários fora de pico e pico, respetivamente. Restrições associadas às ECVEs tais como número de ECVEs por zona e capacidade da ECVE, foram consideradas no modelo. Adicionalmente, são consideradas restrições probabilísticas para a tensão e a corrente pelas linhas. O modelo proposto foi resolvido através de algoritmos genéticos.

Nos trabalhos apresentados previamente, o problema de alocação e dimensionamento das ECVEs é abordado de forma individual, i.e., o problema é resolvido sem considerar o PESD. No entanto, o fato de considerar o planejamento da expansão em conjunto com as ECVEs poderia ser útil, já que o planejamento adequado da rede poderia evitar futuros problemas na operação do sistema. Assim, o OSD estaria preparado para lidar com o aumento da demanda associada ao carregamento dos VEs devido à alta penetração de VEs.

No seguinte capítulo deste trabalho será apresentado um modelo para o problema de PESDM que considera em conjunto, a alocação e dimensionamento de ECVEs.

3 PLANEJAMENTO MULTI-ESTÁGIO DA EXPANSÃO DO SDEE CONSIDERANDO ECVES

Como foi discutido no Capítulo 2, o objetivo principal da solução do problema de PESD é satisfazer de forma adequada o crescimento da demanda minimizando os custos de investimento e operação e respeitando um conjunto de restrições técnicas e operacionais do sistema. Durante os últimos anos, a complexidade do planejamento do SDEE tem aumentado devido à inclusão de novos elementos nas redes de distribuição. Os VEs, por exemplo, representam novas cargas que devem ser atendidas pelas empresas de distribuição, representando novos desafios para os SDEEs. Além disso, o comportamento estocástico, associado aos diferentes elementos que interatuam com os SDEEs, faz com que o problema seja ainda mais complexo.

As ECVEs, também conhecidas como *Parking Lots* ou eletropostos, representam um novo desafio para o planejamento da expansão dos SDEEs. Devido à crescente penetração dos VEs, infraestruturas adequadas de carregamento são necessárias para satisfazer os requerimentos de energia das baterias dos VEs e, além disso, para promover o uso dos VEs como principal meio de transporte, proporcionando um maior nível de confiança aos usuários. Esses requisitos adicionais de energia causados pela integração dos VEs nas redes, além das demandas convencionais, devem ser atendidos pelos OSDs, tendo em conta que a operação adequada do sistema deve ser mantida (HU; SONG, 2012; (LIU; WEN; LEDWICH, 2013; ZHENG et al., 2014). Nesse contexto, o problema de PESDM deveria também considerar a alocação e dimensionamento de ECVEs, as quais forneceriam a energia requerida pelos VEs.

Dado que o PESDM é naturalmente representado por um modelo de PNLIM, neste capítulo será mostrado o modelo original e seguidamente, as linearizações necessárias para obter um modelo de PLIM. Posteriormente, será apresentado um modelo robusto para o problema de PESDM visando levar em consideração as incertezas associadas à demanda convencional e dos VEs usando restrições probabilísticas. É importante mencionar que os modelos matemáticos apresentados neste capítulo foram desenvolvidos e publicados em (BANOL ARIAS et al., 2018).

3.1 CONSIDERAÇÕES PARA A MODELAGEM DAS ECVES

Para a inclusão das ECVEs dentro do problema de PESDM é necessário representar de forma adequada sua operação, que está diretamente relacionada com o processo de carregamento dos VEs. Entranto, o processo de carregamento dos VEs nas ECVEs é um problema de operação que precisa de informações detalhadas relacionadas principalmente com o comportamento dos usuários de VEs, por exemplo, horários de chegada e saída dos VEs, o estado de carga inicial das baterias, requerimentos mínimos de energia, tempos de carregamento, entre outros. Dado o nível de detalhe requerido para representar a operação das ECVEs, a formulação do carregamento de VEs dentro do problema de PESDM é altamente complexa. Assim, visando enfrentar esse desafio, algumas hipóteses são propostas, facilitando o desenvolvimento do modelo matemático do problema de PESDM, que inclui a alocação e dimensionamento de ECVEs, como descrito a seguir:

- Os tópicos relacionados à operação das ECVEs como, por exemplo, os diferentes horários de chegada e/ou saída dos VEs, tempos de espera e/ou tempos de ócio, e a coordenação do carregamento, são simplificados, assumindo que a potência correspondente às ECVEs é demandada de forma agregada em um dia típico, durante um período de tempo específico. Ou seja, as ECVEs operam de forma similar aos postos de gasolina convencionais, considerando um horário fixo de atendimento aos usuários durante o dia. Esse período de tempo é representado dentro da formulação pelo parâmetro dw^{cs}, e corresponde ao número de horas de atendimento por dia.
- Assume-se que não todos os VEs chegam à ECVE ao mesmo tempo e, além disso, assume-se que, o processo de carregamento dos VEs segue a sequência *"first come, first serve"*, a qual é uma das políticas adotadas na teoria de filas (ADAN; RESING, 2002). Assim, se um VE chega e todos os carregadores estão sendo usados, então o VE terá de esperar até algum carregador ficar disponível. Os VEs são carregados na sua ordem de chegada.
- Dado que os VEs possuem diferentes estados de carga (SOC) ao chegar à ECVE que dependem do tipo de VE, da distância diária percorrida, e de outros aspectos relacionados com o comportamento dos proprietários de VEs, é definido um fator conjunto para sua representção. Esse fator corresponde ao parâmetro ϕ_{SOC}, considerado como o valor médio do SOC da bateria dos VEs no momento em que

chegam à ECVE para ser carregados. O SOC é usualmente considerado como uma variável que segue uma função de distribuição de probabilidade Gaussiana.

A formulação proposta identifica a solução ótima para as ECVEs, i.e., a alocação e o número mínimo de carregadores de cada tipo requeridos para atender a demanda associada aos VEs em cada estágio, ao longo do horizonte de planejamento. Com o objetivo de representar o pior caso na operação do SDEE, assume-se que os carregadores se encontram conectados simultaneamente e demandam sua potência nominal desde a rede. As seguintes considerações são feitas visando formular o modelo matemático para o problema de PESDM considerando ECVEs:

- Dada uma penetração de VEs em cada estágio do horizonte de planejamento, a alocação e dimensionamento das ECVEs é proposta pelo operador do SDEE, como foi considerado em Hu e Song, (2012), Liu, Wen e Ledwich (2013), Zheng et al., (2014) e Neyestani et al., (2015). Esta ideia vem do fato de que os SDEEs devem estar preparados para satisfazer os requerimentos de carga causados pelo aumento esperado da demanda associada aos VEs;
- Uma parcela dos VEs é carregada em ECVEs e a outra parcela é carregada nas residências, somando-se esta última à demanda convencional;
- Os VEs podem ser carregados usando dois tipos de carregadores (carregadores rápidos e carregadores lentos) os quais operam de acordo com os níveis de carregamento descritos na seção 2.2.3.

A solução fornecida pelo modelo indicará além da alocação e dimensionamento das ECVEs, os investimentos que devem ser feitos para atender a demanda, junto com o correspondente estágio no horizonte de planejamento. A solução ótima deve minimizar os custos de investimento e operação do SDEE, ao mesmo tempo em que as perdas de energia sejam minimizadas.

3.2 MODELO MATEMÁTICO

O problema de PESDM pode ser matematicamente modelado como um problema de PNLIM, o qual é altamente complexo e de difícil solução. Portanto, devido à complexidade na solução deste tipo de modelos, existem técnicas de linearização que podem ser usadas para transformar o modelo de PNLIM em um modelo de PLIM. Neste capítulo propõe-se inicialmente um modelo de PNLIM para o problema de PESDM baseado no trabalho apresentado em Tabares et al., (2016). Seguidamente, aplicam-se algumas técnicas de linearização visando obter um modelo de PLIM que represente de forma adequada e eficiente o problema de PESDM. A solução do modelo matemático fornecerá as seguintes ações de planejamento:

- Construção e/ou reforço de subestações, em que o reforço se refere ao incremento da capacidade das subestações;
- Construção e/ou recondutoramento de circuitos, em que o recondutoramento refere-se à troca do condutor;
- Alocação de Bancos de Capacitores (BCs);
- Alocação de unidades de Geração Distribuída (GDs);
- Reconfiguração da rede;
- Alocação e dimensionamento das ECVEs, ou seja, o lugar em que será construída a ECVE, e o número mínimo de carregadores a serem instalados em cada ECVE.

A seguir é apresentado o modelo matemático proposto para o problema de PESDM considerando alocação e dimensionamento de ECVEs.

3.2.1 Função Objetivo

No problema de PESD o objetivo principal é minimizar os custos totais de expansão, os quais envolvem os custos de investimento e operação, assim como o custo das perdas de energia ao longo do horizonte de planejamento. Dado que neste caso resolve-se a instância multi-estágio do problema de PESD, esses custos são calculados em cada um dos estágios em que é dividido o horizonte de planejamento e, são levados ao valor presente líquido através de uma função que calcula o valor presente de um custo anual, que será descrita mais para frente. Os custos totais de expansão são representados por (1) e os elementos que a compõem são descritos como segue:

- Custo de construção e/ou reforço de subestações (IS_u), (2);
- Custo de construção e/ou recondutoramento de circuitos (IC_u), (3);
- Custo de instalação de Bancos de Capacitores (IBC_u), (4);
- Custo de instalação de unidades de GDs (IGD_u), (5);
- Custo de instalação de ECVEs ($IECV_u$), (6);

- Custo da energia fornecida pela subestação e pelas unidades de GD, o qual inclui o custo das perdas de energia nos circuitos (CE_u), (7);
- Custo de operação das subestações (OS_u), (8).

$$\min \frac{1}{(1+\tau)^{-(u-1)K}} \sum_u \left(IS_u + IC_u + IBC_u + IGD_u + IECV_u + CE_u + COS_u \right) \tag{1}$$

$$IS_u = \sum_s \sum_h \sum_t c^s_{s,h,t} x^{sub}_{s,h,t,u} \qquad \forall u \in U \tag{2}$$

$$IC_u = \sum_{ij} \sum_a \sum_b c^c_{ij,a,b} x^{cir}_{ij,a,b,u} l_{ij} \qquad \forall u \in U \tag{3}$$

$$IBC_u = \sum_i \left(c^{cb} x^{cb}_{i,u} + c^{mod} n^{cbi}_{i,u} \right) \qquad \forall u \in U \tag{4}$$

$$IGD_u = \sum_m \sum_g c^{dg}_g x^{dg}_{m,g,u} \qquad \forall u \in U \tag{5}$$

$$IECV_u = \sum_p \sum_e \left(c^{cs} x^{cs}_{p,u} + c^c_e n^{chi}_{p,e,u} \right) \qquad \forall u \in U \tag{6}$$

$$CE_u = \alpha \phi_l \left(\sum_s c^e P^S_{s,u} + \sum_m \sum_g c^{edg}_g P^{DG}_{m,u} \right) \zeta(\tau, K) \qquad \forall u \in U \tag{7}$$

$$OS_u = \alpha \phi^s c^{vs} \left(\sum_s S^2_{s,u} \right) \zeta(\tau, K) \qquad \forall u \in U \tag{8}$$

O conjunto de equações apresentados anteriormente é escrito em termos das seguintes variáveis e parâmetros:

$x^{sub}_{s,h,t,u}$	Construção/reforço de subestações no nó *s*, usando o tipo de subestação *t* e assumindo o tipo inicial *h*, no estágio *u*. (Variável binária)
$c^s_{s,h,t}$	Custo de construção/reforço de subestações.
$x^{cir}_{ij,a,b,u}$	Construção/recondutoramento de circuitos na linha *ij*, usando o tipo de cabo *b* e assumindo o tipo inicial *a*, no estágio *u*. (Variável binária)
$c^c_{ij,a,b}$	Custo de construção/recondutoramento de circuitos.
l_{ij}	Comprimento do circuito *ij.*
$x^{cb}_{i,u}$	Instalação de BCs no nó *i*, no estágio *u*. (Variável binária)
c^{cb}	Custo de instalação de um BC.
$n^{cbi}_{i,u}$	Número de módulos instalados em cada BC’. (Variável inteira)

c^{mod}	Custo por módulo instalado em cada BC.
$x^{dg}_{m,g,u}$	Instalação de unidades de GD no nó m, do tipo g, no estágio u. (Variável binária)
c^{dg}_{g}	Custo de instalação de unidades de GD do tipo g.
$x^{cs}_{p,u}$	Instalação de ECVEs no nó p, no estágio g. (Variável binária)
c^{cs}	Custo de instalação de ECVEs.
$n^{chi}_{p,e,u}$	Número de carregadores do tipo e instalados em uma ECVEs. (Variável inteira)
c^{c}_{e}	Custo por carregador instalado em cada ECVE.
$P^{S}_{s,u}$	Potência ativa fornecida pela subestação. (Variável contínua)
c^{e}	Custo da energia fornecida pela subestação.
$P^{DG}_{m,u}$	Potência gerada pelas unidades de GD. (Variável contínua)
c^{edg}_{g}	Custo da energia fornecida pelas unidades de GD.
α	Número de horas durante um ano.
ϕ_{l}	Fator de carga.
ϕ^{s}	Fator de perdas.
c^{vs}	Custo de operação das subestações.
$S^{2}_{s,u}$	Quadrado da potência aparente suprida pela subestação. (Variável contínua)

A função $\varsigma(\tau, K) = (1 - (1 + \tau)^{-K})\tau^{-1}$ presente nas equações (7) e (8), é usada para calcular o valor presente líquido de um custo anualizado com uma duração de K anos e uma taxa de juros τ.

O conjunto U representa cada um dos estágios em que é divido o horizonte de planejamento.

3.2.2 Restrições

No modelo proposto são considerados quatro tipos de restrições:

- Restrições fundamentais dos SDEEs que representam as leis de Kirchhoff, consideradas no fluxo de potência;
- Restrições operacionais do sistema como são limites de tensão, capacidade de corrente nos alimentadores, operação dos BCs e das fontes de GD;
- Restrições lógicas que permitem a coordenação entre os investimentos e a operação do sistema;

- Restrições associadas à alocação e dimensionamento das ECVEs.

3.2.2.1 Restrições fundamentais dos SDEEs

As equações (9)−(12) correspondem às leis de Kirchhoff e representam a operação de SDEE radiais (GONÇALVES, 2013).

$$\sum_{kj}\sum_{a} P_{kj,a,u} - \sum_{ij}\sum_{a}(P_{ij,a,u} + R_a l_{ij} I^2_{ij,a,u}) + P^S_{i,u} + \sum_{g} P^{DG}_{i,g,u} = P^D_{i,u} + \sum_{e} n^{cho}_{i,e,u} P^{ch}_e \quad \forall i \in N \;\; \forall u \in U \qquad (9)$$

$$\sum_{kj}\sum_{a} Q_{kj,a,u} - \sum_{ij}\sum_{a}(Q_{ij,a,u} + X_a l_{ij} I^2_{ij,a,u}) + n^{bco}_{i,u} Q^{cb} + Q^S_{i,u} + \sum_{g} Q^{DG}_{i,g,u} = Q^D_{i,u} \quad \forall i \in N \;\; \forall u \in U \qquad (10)$$

$$V^2_{j,u} I^2_{ij,a,u} = P^2_{ij,a,u} + Q^2_{ij,a,u} \quad \forall ij \in L \;\; \forall u \in U \qquad (11)$$

$$\left| V^2_{i,u} - V^2_{j,u} - \sum_{a}\left[\left(2R_a P_{ij,a,u} + X_a Q_{ij,a,u}\right) l_{ij} + Z^2_a l^2_{ij} I^2_{ij,a,u}\right] \right| \le \left(\overline{V}^2 - \underline{V}^2\right) \sum_{a} (1 - y^{cir}_{ij,a,u}) \quad \forall ij \in L \;\; \forall u \in U \qquad (12)$$

As equações (9) e (10) representam o balanço de potência ativa e reativa e asseguram que todas as demandas do sistema sejam atendidas, i.e., a primeira lei de Kirchhoff. A equação (11) calcula a magnitude da corrente através do circuito ij e a equação (12) define a queda de tensão através do circuito ij em termos do estado de conexão representado pela variável binária ($y^{cir}_{ij,a,u}$), os fluxos de potência ativa e reativa ($P_{ij,a,u}$ e $Q_{ij,a,u}$) e o quadrado da corrente ($I^2_{ij,a,u}$). Estas variáveis são diferentes de zero se e somente se, é escolhido o condutor do tipo a, ou seja $y^{cir}_{ij,a,u}$ igual a 1. Assim, (11) e (12) representam a segunda lei de Kirchhoff para cada laço fundamental.

A demanda associada aos VEs encontra-se no lado direito da equação (9) e é representada como o produto da potência ativa nominal de cada tipo de carregador (P^{ch}_e) e o número de carregadores operando em cada ECVE ($n^{cho}_{i,e,u}$).

O conjunto de equações acima apresentado usa, além dos já descritos, os seguintes parâmetros e variáveis:

$P^D_{i,u}$	Demanda de potência ativa no nó i.
$Q^D_{i,u}$	Demanda de potência reativa no nó i.
R_a	Resistência por comprimento do condutor tipo a.

X_a	Reatância por comprimento do condutor tipo *a*.
z_a	Impedância por comprimento do condutor tipo *a*.
$n_{i,u}^{bco}$	Número de módulos operando em cada BC. (Variável inteira)
Q^{cb}	Potência reativa de cada módulo do BC.
$Q_{i,g,u}^{DG}$	Potência reativa suprida pela unidade de GD. (Variável contínua)
$\underline{V}$	Limite mínimo de tensão.
$\overline{V}$	Limite máximo de tensão.
$V_{j,u}^2$	Quadrado da tensão no nó *i*. (Variável contínua)

Os conjuntos N e L representam o conjunto dos nós e das linhas do SDEE, respetivamente.

3.2.2.2 Restrições operacionais

As restrições (13) e (14) representam os limites de potência aparente dos transformadores da subestação. A potência aparente total suprida pela subestação depende do quadrado da potência ativa e reativa, $P_{s,u}^S$ e $Q_{s,u,}^S$, respetivamente. Além disso, possui um limite máximo de geração escrito em termos da variável de operação da subestação com o correspondente tipo de investimento t, ($y_{s,t,u}^{sub}$) e da sua potência máxima ($\bar{S}_t$). O limite de tensão é definido por (15) enquanto (16) e (17), definem o limite de corrente em termos da capacidade do condutor e do estado de operação do circuito (representado pelas variáveis binárias auxiliares $y_{ij,u}^+$ e $y_{ij,u,}^-$ que indicam a direção do fluxo de potência pelo circuito *ij*), respetivamente.

$$S_{s,u}^2 = \left(P_{s,u}^S\right)^2 + \left(Q_{s,u}^S\right)^2 \qquad \forall s \in SE, \forall u \in U \qquad (13)$$

$$S_{s,u}^2 \le \sum_t \overline{S}_t^2 y_{s,t,u}^{sub} \qquad \forall s \in SE, \forall u \in U \qquad (14)$$

$$\underline{V}^2 \le V_{i,u}^2 \le \overline{V}^2 \qquad \forall i \in N, \forall u \in U \qquad (15)$$

$$0 \le I_{ij,a,u}^2 \le \overline{I}_a^2 y_{ij,a,u}^{cir} \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \qquad (16)$$

$$0 \le I_{ij,a,u}^2 \le \overline{I}_a^2 (y_{ij,u}^+ + y_{ij,u}^-) \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \qquad (17)$$

Além das restrições anteriores, existe outro conjunto de restrições necessário para definir os limites operacionais das subestações e dos circuitos. Assim, o conjunto de equações (18)–(21) limita o fluxo de potência ativa e reativa pelos circuitos que conectam uma subestação, se e somente se, a subestação é construída.

$$P_{ij,a,u} \leq \overline{VI}_a \sum_h \sum_t y_{i,h,t,u}^{sub} \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \,/\, i \in SE \qquad (18)$$

$$P_{ij,a,u} \leq \overline{VI}_a \sum_h \sum_t y_{j,h,t,u}^{sub} \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \,/\, j \in SE \qquad (19)$$

$$Q_{ij,a,u} \leq \overline{VI}_a \sum_h \sum_t y_{i,h,t,u}^{sub} \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \,/\, i \in SE \qquad (20)$$

$$Q_{ij,a,u} \leq \overline{VI}_a \sum_h \sum_t y_{j,h,t,u}^{sub} \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \,/\, j \in SE \qquad (21)$$

Por outro lado, o conjunto de equações (22)–(24) define os limites do fluxo de potência ativa e reativa no circuito *ij*, dependendo do seu estado de operação (variáveis $y_{ij,u}^{+}, y_{ij,u}^{-}$) enquanto (25) e (26) definem os limites do fluxo de potência ativa e reativa em termos da capacidade do condutor (FRANCO; RIDER; ROMERO, 2014).

$$P_{ij,a,u} \leq \overline{VI}_a y_{ij,u}^{+} \qquad \forall ij \in L, \forall a \in A, \forall u \in U \qquad (22)$$

$$P_{ij,a,u} \geq -\overline{VI}_a y_{ij,u}^{-} \qquad \forall ij \in L, \forall a \in A, \forall u \in U \qquad (23)$$

$$\left|Q_{ij,a,u}\right| \leq \overline{VI}_a (y_{ij,u}^{+} + y_{ij,u}^{-}) \qquad \forall ij \in L, \forall a \in A, \forall u \in U \qquad (24)$$

$$\left|P_{ij,a,u}\right| \leq \overline{VI}_a y_{ij,a,u}^{cir} \qquad \forall i \in N, \forall u \in U \qquad (25)$$

$$\left|Q_{ij,a,u}\right| \leq \overline{VI}_a y_{ij,a,u}^{cir} \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \qquad (26)$$

Nas equações descritas nesta subseção, *SE* representa o conjunto dos nós da subestação, e *A* representa o conjunto de alternativas para os tipos de condutores.

3.2.2.3 Restrições operacionais das unidades de GD

O conjunto de restrições (27)–(32) permite coordenar a operação das unidades de GD baseados no trabalho desenvolvido por Franco, Rider e Romero (2015). Assim, (27) e (28) definem os limites mínimos e máximos de potência ativa e reativa gerada pelas unidades de GD, respectivamente. A potência ativa é limitada pela potência aparente de cada tipo g $\left(S_g^{DG}\right)$ e a correspondente variável de alocação, enquanto o limite de potência reativa depende da potência ativa gerada $\left(P_{m,g,u}^{DG}\right)$ e do fator de potência $\left(\phi_g^{dg}\right)$ da unidade de GD. A restrição (29) permite a alocação de somente um tipo de GD em cada nó do sistema, enquanto (30) estabelece que uma unidade de GD possa ser alocada somente uma vez durante o horizonte de planejamento. A restrição (31) permite alocar somente uma unidade de GD em cada nó e finalmente (32) limita a quantidade de demanda que pode ser atendida pelas unidades de DG, de acordo com a porcentagem de penetração ($\%^{dg}$).

$$0 \le P_{m,g,u}^{DG} \le S_g^{DG} x_{m,g,u}^{dg} \qquad \forall m \in M, \forall g \in G\ \forall u \in U \quad (27)$$

$$\left|Q_{m,u}^{DG}\right| \le P_{m,g,u}^{DG} tg\left(\cos^{-1}\phi_g^{dg}\right) \qquad \forall m \in M, \forall g \in G\ \forall u \in U \quad (28)$$

$$\sum_g x_{m,g,u}^{dg} \le 1 \qquad \forall m \in M, \forall u \in U \quad (29)$$

$$x_{m,g,u}^{dg} \le \sum_{k=1}^{u} x_{m,g,k}^{dg} \qquad \forall m \in M, \forall g \in G\ \forall u \in U \quad (30)$$

$$\sum_u \sum_g x_{m,g,u}^{dg} \le 1 \qquad \forall m \in M \quad (31)$$

$$\sum_m \sum_g P_{m,g,u}^{DG} \le \%^{dg} \sum_i P_{i,u}^{D} \qquad \forall u \in U \quad (32)$$

O conjunto *M* representa o conjunto dos nós disponíveis para alocação de unidades de GD e o conjunto *G* representa os tipos de GD.

3.2.2.4 Restrições operacionais dos BCs

A modelagem dos BCs é baseada no trabalho apresentado em Franco et al., (2013) considerando-se a utilização de bancos de capacitores fixos, em que todos os módulos de um mesmo BC possuem a mesma capacidade. Assim, (33) permite a instalação de um módulo se e somente se, a decisão de alocar um BC já foi realizada no estágio atual ou em estágios prévios, de acordo com o número máximo de módulos permitidos em cada BC ($\overline{N}$). Por outro lado, (34) limita o número de módulos em operação em um nó, de acordo com o número de módulos instalados. A restrição (35) estabelece que a alocação de um BC possa ser feita somente uma vez ao longo do horizonte de planejamento enquanto (36) indica que existe uma quantidade máxima de BCs ($\overline{N}$) que podem ser alocados em todo o sistema.

$$\sum_{k=1}^{u} n_{i,u}^{cbi} \le \overline{N} \sum_{k=1}^{u} x_{i,k}^{cb} \qquad \forall i \in NBC, \forall u \in U \quad (33)$$

$$n_{i,u}^{cbo} \le \sum_{k=1}^{u} n_{i,k}^{cbi} \qquad \forall i \in NBC, \forall u \in U \quad (34)$$

$$\sum_{u} x_{i,u}^{cb} \le 1 \qquad \forall i \in NBC \quad (35)$$

$$\sum_{u}\sum_{i} x_{i,u}^{cb} \le \overline{\mathrm{M}} \quad (36)$$

3.2.2.5 *Restrições da operação radial dos SDEE*

As restrições (37)−(38), em conjunto com (9) e (10), garantem a operação radial do sistema (LAVORATO et al., 2012). Este conjunto de equações considera a presença de nós de transferência os quais são usados para representar nós sem geração ou demanda e que normalmente conectam um nó de demanda com outros nós (TABARES et al., 2016). Os nós de transferência são representados pela variável binária $\wp_{i,u}$, igual a 1 se o nó é usado como nó de transferência, ou zero em caso contrário. Nesse conjunto de equações NT representa o conjunto de nós de transferência.

$$\sum_{ij}\left(y_{ij,u}^{+} + y_{ij,u}^{-}\right) = |N| - |SE| - \sum_{j \in NT}(1 - \wp_{j,u}) \qquad \forall u \in U \quad (37)$$

$$\sum_{ij}\left(y_{ij,u}^{+} + y_{ij,u}^{-}\right) + \sum_{ji}\left(y_{ji,u}^{+} + y_{ji,u}^{-}\right) \ge 2\wp_{j,u} \qquad \forall i \in NT,\ \forall u \in U\ / P_{i,u}^{D} = 0 \vee Q_{i,u}^{D} = 0 \quad (38)$$

$$y_{ij,u}^{+} + y_{ij,u}^{-} \le \wp_{j,u} \qquad \forall ij \in L\ /\ j \in NT, \forall u \in U \quad (39)$$

$$y_{ji,u}^{+} + y_{ji,u}^{-} \le \wp_{j,u} \qquad \forall ji \in L\ /\ j \in NT,\ \forall u \in U \quad (40)$$

3.2.2.6 *Restrições lógicas associadas às subestações*

O conjunto de restrições (41)–(45) permite a coordenação entre os investimentos e a operação das subestações ao longo do horizonte de planejamento. A variável binária $x_{s,h,t,u}^{sub}$ representa a opção de construir e/ou reforçar uma subestação usando o tipo *t*, desde um tipo inicial *h*. Neste tipo de formulação os tipos de subestações estão ordenados ascendentemente, de acordo com a capacidade de potência e os custos de investimento. Assim, somente são permitidas transições nas quais *t* é maior do que *h*.

$$\sum_{h}\sum_{t} x_{s,h,t,u}^{sub} \le 1 \qquad \forall s \in SE, \forall u \in U \quad (41)$$

$$\sum_{u} x_{s,h,t,u}^{sub} \le 1 \qquad \forall s \in SE, \forall h \in T\ \forall t \in T \quad (42)$$

$$x_{s,h,t,u}^{sub} \le \theta_{s,h}^{sub} + \sum_{k=1}^{u-1}\sum_{r} x_{s,r,h,k}^{sub} \qquad \forall s \in SE, \forall h \in T\ \forall t \in T, \forall u \in U \quad (43)$$

$$y_{s,t,u}^{sub} \leq \theta_{s,t}^{sub} + \sum_{k=1}^{u} \sum_{h} x_{s,h,t,k}^{sub} \qquad \forall s \in SE, \forall t \in T \ \forall u \in U \qquad (44)$$

$$\sum_{t} y_{s,t,u}^{sub} \leq 1 \qquad \forall s \in SE, \forall u \in U \qquad (45)$$

Nas restrições apresentadas acima, (41) habilita somente um tipo investimento por estágio, enquanto (42) garante que um investimento específico em uma subestação (desde h para t) seja feito somente uma vez durante o horizonte de planejamento. A restrição (43) estabelece que o reforço de uma subestação usando o tipo inicial h possa ser feito se, e somente se, esse tipo foi usado para construir e/ou reforçar a subestação em estágios anteriores. O parâmetro binário $\theta_{s,h}^{sub}$ representa o estado inicial da subestação ao começo do horizonte de planejamento, o qual é 1 se a subestação estava construída e, zero em caso contrário. Finalmente (44) garante que a operação da subestação seja realizada somente se o correspondente investimento foi feito, enquanto (45) permite a operação da subestação usando somente um tipo de investimento em cada estágio. T representa o conjunto de alternativas de investimento nas subestações.

3.2.2.7 Restrições lógicas associadas aos circuitos

As restrições (46)–(50) permitem a coordenação entre os investimentos e a operação dos circuitos ao longo do horizonte de planejamento. Este conjunto de restrições segue a mesma estrutura lógica das restrições associadas à coordenação em investimentos e operação das subestações. Os tipos de investimento correspondem ao conjunto de capacidades disponíveis para construir e/ou reforçar os circuitos. Assim, a construção e/ou recondutoramento de um circuito usando o tipo b a partir do tipo inicial a, é representado pela variável binária $x_{ij,a,b,u}^{cir}$. Os tipos de circuitos estão ordenados ascendentemente, de acordo com a capacidade de corrente e os custos de investimento. Assim, somente são permitidas transições nas quais b é maior do que a. A operação de um circuito usando tipo b é representada pela variável binária $y_{ij,,b,u}^{cir}$, e o parâmetro binário $\theta_{ij,a}^{cir}$ representa o estado inicial do circuito no começo do horizonte de planejamento, o qual é 1 se o circuito estava construído e, zero no caso contrário. Por último, (51) é incluída dentro do modelo visando melhorar seu desempenho como apresentado em Franco et al., (2013).

$$\sum_{a}\sum_{b} x_{ij,a,b,u}^{cir} \leq 1 \qquad \forall ij \in L, \forall u \in U \quad (46)$$

$$\sum_{u} x_{ij,a,b,u}^{cir} \leq 1 \qquad \forall ij \in L, \forall a \in A\ \forall b \in A \quad (47)$$

$$x_{ij,a,b,u}^{cir} \leq \theta_{ij,a}^{cir} + \sum_{k=1}^{u-1}\sum_{c} x_{ij,c,a,k}^{cir} \qquad \forall ij \in L, \forall a \in A\ \forall b \in A, \forall u \in U \quad (48)$$

$$y_{ij,b,u}^{cir} \leq \theta_{ij,b}^{cir} + \sum_{k=1}^{u}\sum_{a} x_{ij,a,b,u}^{cir} \qquad \forall ij \in L, \forall b \in A\ \forall u \in U \quad (49)$$

$$\sum_{b} y_{ij,b,u}^{cir} \leq 1 \qquad \forall ij \in L, \forall u \in U \quad (50)$$

$$\sum_{b} y_{ij,b,u}^{cir} = y_{ij,u}^{+} + y_{ij,u}^{-} \qquad \forall ij \in L, \forall u \in U \quad (51)$$

Nas equações apresentadas acima, A representa o conjunto de alternativas de investimento nos circuitos.

3.2.2.8 Modelagem matemática das ECVEs

O conjunto de equações (52)–(56) usado para modelar as ECVEs foi desenvolvido de acordo com os supostos apresentados na Seção 3.1. A restrição (52) garante a alocação de uma ECVS em um nó do SDEE somente uma vez durante o horizonte de planejamento, enquanto (53) permite a instalação de carregadores considerando um número máximo de carregadores $(\bar{C}_p)$ somente se a ECVE já foi alocada. A restrição (54) limita o número de carregadores operando em cada estágio do horizonte de planejamento de forma tal que não excedam o número de carregadores que já foram instalados.

$$\sum_{u} x_{p,u}^{cs} \leq 1 \qquad \forall p \in P \quad (52)$$

$$\sum_{e}\sum_{k=1}^{u} n_{p,e,k}^{chi} \leq \bar{C}_p \sum_{k=1}^{u} x_{p,k}^{cs} \qquad \forall p \in P, \forall u \in U \quad (53)$$

$$n_{p,e,u}^{cho} \leq \sum_{k=1}^{u} n_{p,e,k}^{chi} \qquad \forall p \in P, \forall e \in E\ \forall u \in U \quad (54)$$

A equação (55) relaciona o número de VEs do tipo v que precisam ser carregados $(N_{v,u}^{EV})$ com o número de VEs que são atribuídos a diferentes tipos de carregadores $(n_{e,v,u}^{ev})$. A equação (55) está escrita em termos do valor médio do número de VEs de cada tipo que precisam ser carregados em cada estágio $(N_{v,u}^{EV})$, do desvio padrão do número de VEs $(\sigma_{v,u}^{EV})$, e do fator de robustez $\phi(\varepsilon)$ que corresponde à área sob a curva de distribuição normal para um nível de confiança especificado $1-\varepsilon$. Dessa forma, (55) considera o comportamento estocástico associado à penetração de VEs em cada estágio. Por outro lado, deve ser mencionado que para os casos em que $\sigma_{v,u}^{EV}$ é igual a cero, (55) é transformada automaticamente em uma equação determinística, escrita somente em termos do número de VEs do tipo v que precisam ser carregados em cada estágio. Finalmente, a restrição (56) estabelece que a energia que pode ser suprida pelos carregadores durante seu tempo de operação dw^{cs}, deveria satisfazer a energia requerida pelos VEs. A restrição (56) está escrita em termos da potência nominal do carregador de tipo e (P_e^{ch}), a energia requerida por um VE de tipo v $\left(E_v^{req}\right)$, e a diferença entre o máximo SOC do VE (ϕ_{soc}^{max}) e o fator que representa o SOC dos VEs na hora da chegada na ECVE (ϕ_{SOC}) .

$$\sum_{e} n_{e,v,u}^{ev} = N_{v,u}^{EV} + \phi(\varepsilon)\sigma_{v,u}^{EV} \qquad \forall v \in V, \forall u \in U \quad (55)$$

$$\sum_{p} P_e^{ch} n_{p,e,u}^{cho} dw^{cs} \geq \sum_{v} n_{e,v,u}^{ev} E_v^{req} \left(\phi_{soc}^{\max} - \phi_{soc}\right) \qquad \forall e \in E, \forall u \in U \quad (56)$$

P, E e *V* representam os conjuntos de nós onde podem ser instaladas ECVEs, tipos de carregadores e tipos de VEs, respetivamente.

Vale a pena mencionar que os VEs são considerados como cargas, ou que significa que as baterias somente podem ser carregadas e não estão habilitadas para fornecer potência à rede. Isso resulta em um consumo de potência refletido no lado direito da equação de balanço de potência ativa (9). Deste modo, o conjunto de equações e restrições (1)–(56) corresponde a um modelo de PNLIM para o problema de PESDM considerando as ECVEs.

3.2.3 Transformação do modelo original em um modelo de PLIM

O modelo anteriormente proposto corresponde a um modelo PNLIM devido à presença de variáveis quadráticas e produtos entre variáveis. Note-se que na função objetivo, representada por (8), aparece a variável $S_{s,u}^2$ e que nas equações (9)–(17) aparecem as variáveis $I_{ij,a,u}^2$ e $V_{i,u}^2$. Através de uma troca de variáveis é possível obter uma representação linear das equações (8)–(17) como proposto em Gonçalves et al., (2013). Assim, as variáveis originais $S_{s,u}^2$, $I_{ij,a,u}^2$ e $V_{i,u}^2$, são substituídas pelas novas variáveis $S_{s,u}^{sqr}$, $I_{ij,a,u}^{sqr}$ e $V_{i,u}^{sqr}$, respetivamente, dando como resultado o seguinte conjunto de equações:

$$OS_u = \alpha\phi^s c^{vs}\left(\sum_s S^{sqr}_{s,u}\right)\zeta(\tau, K) \qquad \forall u \in U \qquad (57)$$

$$\sum_{kj}\sum_a P_{kj,a,u} - \sum_{ij}\sum_a (P_{ij,a,u} + R_a l_{ij} I^{sqr}_{ij,a,u}) + P^S_{i,u} + \sum_g P^{DG}_{i,g,u} = P^D_{i,u} + \sum_e n^{cho}_{i,e,u} P^{ch}_e \qquad \forall i \in N\ \forall u \in U \qquad (58)$$

$$\sum_{kj}\sum_a Q_{kj,a,u} - \sum_{ij}\sum_a (Q_{ij,a,u} + X_a l_{ij} I^{sqr}_{ij,a,u}) + n^{bco}_{i,u} Q^{cb} + Q^S_{i,u} + \sum_g Q^{DG}_{i,g,u} = Q^D_{i,u} \qquad \forall i \in N\ \forall u \in U \qquad (59)$$

$$V^{sqr}_{j,u} I^{sqr}_{ij,a,u} = P^2_{ij,a,u} + Q^2_{ij,a,u} \qquad \forall ij \in L\ \forall u \in U \qquad (60)$$

$$\left| V^{sqr}_{i,u} - V^{sqr}_{j,u} - \sum_a \left[\left(2R_a P_{ij,a,u} + X_a Q_{ij,a,u}\right) l_{ij} + Z^2_a l^{sqr}_{ij} I^2_{ij,a,u}\right]\right| \le \left(\overline{V}^2 - \underline{V}^2\right)\sum_a (1 - y^{cir}_{ij,a,u}) \qquad \forall ij \in L\ \forall u \in U \qquad (61)$$

$$S^{sqr}_{s,u} = \left(P^S_{s,u}\right)^2 + \left(Q^S_{s,u}\right)^2 \qquad \forall s \in SE, \forall u \in U \qquad (62)$$

$$S^{sqr}_{s,u} \le \sum_t \overline{S}^2_t y^{sub}_{s,t,u} \qquad \forall s \in SE, \forall u \in U \qquad (63)$$

$$\underline{V}^2 \le V^{sqr}_{i,u} \le \overline{V}^2 \qquad \forall i \in N, \forall u \in U \qquad (64)$$

$$0 \le I^{sqr}_{ij,a,u} \le \overline{I}^2_a y^{cir}_{ij,a,u} \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \qquad (65)$$

$$0 \le I^{sqr}_{ij,a,u} \le \overline{I}^2_a (y^+_{ij,u} + y^-_{ij,u}) \qquad \forall ij \in L, \forall a \in A\ \forall u \in U \qquad (66)$$

No entanto, depois do processo de troca de variáveis, é possível observar que (60) ainda apresenta não linearidades em ambos os lados da equação. Assim, o lado esquerdo da equação é linearizado trocando a variável $V^{sqr}_{j,u}$ pelo parâmetro $V'^2_{j,u}$ que representa uma tensão estimada no nó i, de acordo com o apresentado em Tabares et al., (2016). O lado direto da equação foi linearizado a partir da técnica de linearização por partes apresentada em (GONÇALVES, 2013). Assim, a função $f(\rho, \bar{\rho}, \Gamma)$ representa a linearização por partes do quadrado da variável ρ, escrita em termos do seu valor máximo $\bar{\rho}$ e o número de intervalos de discretização Γ, como apresentado detalhadamente no Apêndice A. Logo, a equação (67) é uma equação linear para o cálculo da magnitude de tensão.

$$V'^2_{j,u} I^{sqr}_{ij,a,u} = f\left(P_{ij,a,u}, \overline{VI}_a, \Gamma\right) + f\left(Q_{ij,a,u}, \overline{VI}_a, \Gamma\right) \qquad \forall ij \in L, \forall u \in U \qquad (67)$$

Desse mesmo modo, note-se que (62) é uma equação não linear devido às variáveis quadráticas $\left(P_{s,u}^{S}\right)^2$ e $\left(Q_{s,u}^{S}\right)^2$. Assim, ambas as variáveis são linearizadas usando a função $f(\rho, \bar{\rho}, \Gamma)$ apresentada no Apêndice C. Logo, (68) é uma equação linear que permite calcular a potência aparente suprida pela subestação,

$$S_{s,u}^{sqr} = \sum_{t}\left[f(P_{s,u}^{S}, \bar{S}_t, \Gamma) + f(Q_{s,u}^{S}, \bar{S}_t, \Gamma) \right] \qquad \forall s \in SE, \forall u \in U \qquad (68)$$

Finalmente, o modelo proposto para o problema de PESDM considerando ECVEs corresponde a um modelo de PLIM que pode ser resolvido através de técnicas de otimização clássica para as quais existem softwares eficientes que garantem otimalidade e/ou fornecem medidas de distância à solução ótima. Assim, o modelo determinístico de PLIM para o problema de PESDM considerando ECVEs é representado pelo conjunto de equações e restrições (1)–(7), (18)–(59), (61), (63)–(68).

Dado que um dos objetivos deste trabalho é apresentar uma formulação robusta para o problema, no próximo capítulo serão apresentados alguns conceitos básicos sobre programação estocástica e apresenta-se um modelo robusto que permite considerar a natureza incerta da demanda convencional e dos VEs através da aplicação de restrições probabilísticas, desenvolvidas para definir a capacidade das subestações.

4 MODELAGEM ROBUSTA PARA O PESDM CONSIDERANDO ECVES

Como foi discutido no Capitulo 1, é importante considerar as incertezas associadas às demandas tanto convencionais como dos VEs no planejamento da expansão e operação do SDEE já que pode acontecer que as redes não estejam suficientemente dimensionadas para atender a demanda, arriscando a qualidade do serviço e provocando multas para as concessionárias. Assim, com o objetivo de cobrir essas questões, neste capitulo é desenvolvida e apresentada uma modelagem robusta para o problema de PESDM considerando ECVEs, a fim de obter planos de expansão mais eficientes e confiáveis, e melhor adaptados às condições reais dos SDEEs. O modelo matemático apresentado neste capítulo foi desenvolvido e publicado em Banol Arias et al., (2018).

4.1 CONSIDERAÇÃO DA INCERTEZA

A maioria dos problemas de programação matemática incorporam parâmetros que se supõem ser conhecidos e constantes no momento de resolver o problema. Porém, se o problema de otimização é o resultado da representação através de um modelo de uma situação real na que se deve tomar uma decisão, é comum que os valores de alguns parâmetros sejam desconhecidos. Assim, esse desconhecimento leva à tomada de decisões em que não são avaliadas as possíveis consequências das mesmas. Estes tipos de problemas são comumente resolvidos através da otimização sob incertezas, a qual começou a ser desenvolvida no ano de 1955 com os trabalhos de Dantzing e Beale (DANTZIG, 1955; BEALE, 1955), como uma extensão da programação linear. A otmização sob incertezas analisa a solução de problemas onde alguns dos parâmetros são desconhecidos e se define como a solução de problemas de programação matemática em que alguns ou todos os parâmetros são variáveis aleatórias (PRÉKOPA, 1995).

Entre os métodos usados para resolver problemas de otimização considerando incertezas encontram-se a programação estocástica e a otimização robusta, ambas as duas com diversas vantagens e desvantagens que podem ser utilizadas de acordo com a natureza do problema. A programação estocástica tem como objetivo fornecer uma solução factível para todas, ou quase todas as realizações da incerteza. Esta trabalha sob o suposto de que as distribuições de probabilidade das variáveis incertas são conhecidas ou podem ser calculadas adequadamente e pode ser formulada através da geração de cenários, gestão do risco e/ou modelos avessos ao risco, programação dinâmica estocástica e restrições probabilísticas conhecidas na literatura como *chance-constraints.* Por outro lado, a otimização robusta tem como objetivo fornecer uma solução que seja factível para qualquer realização da incerteza considerada dentro de um conjunto previamente estabelecido e não é permitido nenhum tipo de violação das restrições. Uma das vantagens da otimização robusta é que as distribuições de probabilidade das variáveis incertas não precisam ser conhecidas (ALEM; MORABITO, 2015).

Ambas metodologias podem ser aplicadas dependendo das informações disponíveis e dos requisitos na solução final (OLIVEIRA, 2013).

No contexto do problema de PESDM, muitos dos parâmetros e variáveis associadas ao problema possuem características de natureza incerta. O problema de PESDM está sujeito principalmente ao comportamento estocástico das demandas futuras do sistema durante o horizonte de planejamento. Desta forma, a taxa de crescimento da demanda, assim como também a penetração dos VEs, são de natureza incerta e influenciam fortemente nas decisões de expansão do SDEE. Portanto, se as incertezas associadas às demandas de energia tanto convencional como dos VEs não são consideradas na solução do problema do PESDM, pode acontecer o superdimensionamento do sistema, deixando custos desnecessários para os OSDs ou pelo contrário, que o plano de investimento não seja suficientemente robusto para atender todas as demandas, resultando em energia não suprida no sistema e incorrendo em custos de multas para os OSDs pelo não atendimento das demandas.

Dada a natureza estocástica das demandas futuras do sistema durante o horizonte de planejamento, neste trabalho é usado um método de otimização estocástica baseado em restrições probabilísticas para lidar com as incertezas associadas à demanda, garantindo o cumprimento da capacidade das subestações com um nível de confiança especificado.

4.1.1 Programação com restrições probabilísticas: Conceitos gerais

A programação com restrições probabilísticas é um tipo de otimização estocástica que permite incorporar aleatoriedade em um modelo matemático através de medições probabilísticas sobre restrições incertas (CHARNES; COOPER, 1963). Essas restrições são satisfeitas apenas em uma determinada proporção das vezes, ou seja, são satisfeitas com uma probabilidade específica.

As restrições probabilísticas (RPs) representam uma importante ferramenta quando em algumas realizações de incertezas, alguns objetivos impostos pelo tomador de decisões não podem ser atendidos. Assim, uma decisão é considerada admissível se ela satisfaz as restrições com probabilidade igual ou maior que um grau de confiabilidade determinado definido pelo tomador de decisões.

A formulação matemática típica das RPs será apresentada nesta subseção seguindo um exemplo ilustrativo desenvolvido previamente em Franco, Rider e Romero (2016). Suponha-se o modelo de programação linear genérico representado por (69)−(70), onde *x* é uma variável de decisão e (*A, b, c*) são valores numéricos correspondentes às entradas do problema.

$$\min c^T x \tag{69}$$

$$\text{Subject to}: Ax \leq b \tag{70}$$

Se A tem coeficientes aleatórios tal que suas linhas seguem uma função de distribuição de probabilidade normal com média igual à $\tilde{A}_i$, e uma matriz de covarianza $\sum_i \left(A_i = N\left(\tilde{A}_i, \sum i\right)\right)$, logo, o modelo de programação linear pode ser reformulado para considerar restrições probabilísticas como mostrado em (71)−(72) de acordo com o apresentado em Ben-Tal, El Ghaoui e Nemirovski (2009).

$$\min c^T x \tag{71}$$

$$\text{subject to: } \mathrm{P}\left\{Ax \leq b\right\} \geq 1-\varepsilon \tag{72}$$

A principal diferença entre ambos os modelos é que em (71)−(72) as restrições são modeladas como restrições probabilísticas, ou seja, as restrições devem ser satisfeitas com uma probabilidade preestabelecida definida pelo parâmetro robusto ε. Nesse contexto, a solução desse problema é ε confiável se e somente se (72) é satisfeita.

Assim, assumindo que não existe correlação entre as filas da matriz A, (72) pode ser reescrita como mostrado em (73), sendo que (73) representa um conjunto de restrições não convexas que podem ser transformadas em restrições cônicas de segunda ordem sob algunas condições específicas. Nesse contexto, (74) representa o conjunto de restrições cônicas de segunda ordem se e somente se $\phi(\varepsilon) > 0$ e $\varepsilon > 1/2$, como demonstrado em Ben-Tal, El Ghaoui e Nemirovski (2009).

$$\mathrm{P}\left\{A_i^T x \le b_i\right\} \ge 1-\varepsilon \quad \forall i = 1,\ldots,\mathrm{Rango(A)} \tag{73}$$

$$\hat{A}_i^T x + \phi(\varepsilon)\sqrt{x^T \sum x} \le b_i \quad \forall i = 1,\ldots,\mathrm{Rango(A)} \tag{74}$$

A função $\phi(\varepsilon)$ representa o valor Z padronizado correspondente à área sob a curva de distribuição normal para o percentil $1-\varepsilon$. Pequenos valores de ε resultam em grandes valores de $\phi(\varepsilon)$, fazendo com que (74) seja mais difícil de satisfazer. O termo $\phi(\varepsilon)\sqrt{x^T \sum x}$ pode ser interpretado como um termo de risco, em que $\sqrt{x^T \sum x}$ corresponde ao desvio padrão enquanto A corresponde ao valor médio, como definido em Ben-Tal, El Ghaoui e Nemirovski (2009).

Existem dois tipos de RPs: As RPs individuais e as RPs conjuntas. A diferença entre estes dois tipos é principalmente que as RPs individuais se estabelecem uma por vez, sendo que cada uma representa um objetivo diferente. Nas restrições conjuntas existe um tipo de atendimento simultâneo, ou seja, o conjunto agrupado de restrições individuais representa um único objetivo. Estas últimas são mais difíceis de resolver em termos de custo computacional.

A aplicação desta metodologia é pouco usada devido à alta complexidade computacional, pois nem sempre é garantida a convexidade das restrições. No entanto, existem casos particulares (como o caso do exemplo ilustrativo composto pelas equações (69)–(74)) para os quais a convexidade é garantida (BERTOCCHI; CONSIGLI; DEMPSTER, 2011).

Partindo dos conceitos apresentados acima, é incluído um novo conjunto de equações dentro da formulação proposta para o problema de PESDM considerando alocação e dimensionamento de ECVEs. Restrições probabilísticas para a capacidade da subestação são propostas visando lidar com o comportamento estocástico das demandas.

4.1.2 Restrições probabilísticas para a capacidade da subestação

A restrição (75) é uma RP que considera o comportamento estocástico da demanda convencional e dos VEs. Esta restrição garante o cumprimento da capacidade da subestação com um determinado nível de confiança e está escrita em termos da potência aparente estocástica suprida pela subestação $\left(\tilde{S}_{s,u}\right)$, a capacidade máxima da subestação $(\bar{S}_t)$ e as variáveis de investimento $\left(y_{s,tu}\right)$. Assim, (75) garante que a capacidade da subestação seja satisfeita considerando uma probabilidade relacionada ao parâmetro de robustez ε.

$$Prob\left\{\tilde{S}_{s,u} \leq \sum_t \bar{S}_t y_{s,t,u}^{sub}\right\} \geq 1-\varepsilon \qquad \forall s \in SE\ , \forall u \in U \qquad (75)$$

Como mencionado na subseção 4.1.1, a RP (75) é naturalmente uma restrição não convexa. Assim, dado que um dos objetivos deste trabalho é desenvolver um modelo de PLIM para o problema de PESDM considerando ECVEs, é necessário transformar (75) em uma restrição linear (76) que corresponde ao equivalente linear determinístico, como é proposto em Charnes e Cooper (1963). Assim, (76) é escrita em termos do valor médio $\left(S_{s,u}\right)$ e do desvio padrão $\left(\sigma_{s,u}\right)$ da potência aparente suprida pela subestação, sempre que $\tilde{S}_{s,u}$ siga uma função de distribuição de probabilidade normal. Além disso, $\phi(\varepsilon)$ representa o valor Z padronizado correspondente à área sob a curva de distribuição normal para o percentil $1-\varepsilon$.

$$S_{s,u} + \phi(\varepsilon)\sigma_{s,u} \leq \sum_t \bar{S}_t y_{s,t,u}^{sub} \qquad \forall s \in SE\ , \forall u \in U \qquad (76)$$

Além da dificuldade da RP definida por (75) ser uma expressão não convexa, problema que pode ser abordado através de um equivalente linear determinístico Charnes e Cooper (1963), ainda foram identificadas outras dificultades durante o desenvolvimento das RPs para a capacidade da subestação. A seguir serão descritas as principais dificuldades junto com as soluções propostas para lidar com elas.

4.1.2.1 Relação entre os parâmetros incertos e a potência aparente das subestações

Após encontrar uma expressão linear para a RP (75) dada por (76), é necessário procurar uma expressão que relacione a demanda incerta com a potência aparente suprida pelas subestações, visando obter seu valor médio e seu desvio padrão. No entanto, dado que não existe uma relação explícita entre a demanda de potência ativa e a potência aparente da subestação e além disso, devido à relação não linear entre a potência ativa, reativa e aparente mostrada em (13) e equivalente à $S_{s,u} = \sqrt{{P_{s,u}^{S}}^{2} + {Q_{s,u}^{S}}^{2}}$, o cálculo do valor médio e do desvio padrão de $\tilde{S}_{s,u}$ é altamente complexo.

Para lidar com essas limitações, propõe-se calcular esses valores estimando a potência ativa suprida pela subestação e assumindo um fator de potência (ϕ_{pf}) que permite representar a potência reativa suprida pela mesma. Assim, usando (58) como base, a potência ativa suprida pela subestação pode ser expressa em termos da demanda incerta $(\tilde{P}_{i,u}^{D})$, a demanda dos VEs representada pelo número de carregadores $(n_{i,e,u}^{cho})$ instalados em cada ECVE e a correspondente potência nominal (P_e^{ch}), a potência injetada pelas unidades de GD e as perdas de potência, como é mostrado em (77). Note-se, que em (77) aparece também o termo $\%P^{loss}$, o qual representa as perdas de potência ativa. Assim, assume-se que as perdas de potência ativa correspondem a uma porcentagem da potência ativa total suprida pela subestação.

$$\tilde{S}_{s,u} = \frac{\sum_i \omega_{s,i,u}^{sub} \left[(1+\%P^{loss})\,\tilde{P}_{i,u}^{D} + \sum_e n_{i,e,u}^{cho} P_e^{ch} - \sum_g P_{i,g,u}^{DG} \right]}{\phi_{pf}} \qquad \forall s \in SE, \forall u \in U \qquad (77)$$

4.1.2.2 Identificação dos nós de demanda atendidos por cada subestação

Dado que no problema de planejamento não é conhecido *a priori* quais nós de demanda serão atentidos por cada subestação e, além disso, dado que o modelo proposto considera a possibilidade de reconfigurar a rede de um estágio para outro, existe a necessidade de identificar a demanda total atribuída a cada subestação em cada estágio de planejamento. Para isso foi necessário adicionar uma nova variável binária $\omega_{s,i,u}^{sub}$ que indica se o nó *i* está ligado à subestação *s*. Esta variável é obtida usando (78) e (79), as quais vêm da formulação analítica que encontra o caminho mais curto através de um grafo radial entre cada nó e sua fonte correspondente (LÓPEZ et al., 2016).

Considerando uma demanda artificial em cada nó dada pelo parâmetro binário $f_{i,k,u}^{D}$, que é igual a 1 se a demanda no nó *i* $(P_{i,u}^{D})$ é diferente de zero, e é igual a zero no caso contrário, (78) representa um balanço de fluxos artificias através dos circuitos do sistema. A variável contínua $f_{ij,k,u}$ representa o fluxo artificial que identifica o caminho a montante de cada nó i e sua correspondente fonte k (neste caso k representa a subestação). Além disso, $f_{ij,k,u}$ está relacionado com as variáveis de operação dos circuitos $y^{+}_{ij,u}$ e $y^{-}_{ij,u}$ através de (79).

$$\sum_{ji} f_{ji,k,u} - \sum_{ij} f_{ij,k,u} + \omega^{sub}_{i,k,u} = f^{D}_{i,k,u} \qquad \forall i \in N, \forall k \in N, \forall u \in U \quad (78)$$

$$| f_{ij,k,u} | \leq y^{+}_{ij,u} + y^{-}_{ij,u} \qquad \forall ij \in L, \forall k \in N \;\; \forall u \in U \;/ P^{D}_{k,u} > 0 \quad (79)$$

4.1.2.3 Cálculo do valor médio e do desvio padrão da potência aparente

Seguindo as propriedades da distribuição normal e assumindo que as demandas são variáveis normais independentes, o valor médio da potência aparente é obtido de (77) usando os valores médios das demandas $\left(P^{D}_{i,u}\right)$ como é mostrado em (80).

$$S_{s,u} = \frac{\sum_{i} \omega^{sub}_{s,i,u} \left[(1+\%P^{loss}) P^{D}_{i,u} + \sum_{e} n^{cho}_{i,e,u} P^{ch}_{e} - \sum_{g} P^{DG}_{i,g,u} \right]}{\phi_{pf}} \qquad \begin{array}{c} \forall s \in SE \\ \forall k \in N \\ \forall u \in U \end{array} \quad (80)$$

Por outro lado, a variância da potência aparente mostrada em (81) é também obtida de (77), considerando que, para uma função de distribuição normal, a variância da potência aparente $\left(\sigma^{2}_{s,u}\right)$ corresponde à soma das variâncias das demandas $\left(\sigma^{D}_{i,u}\right)^{2}$.

$$\sigma^{2}_{s,u} = \left[\frac{(1+\%P^{loss})}{\phi_{pf}} \right]^{2} \sum_{i} \sigma^{D\,2}_{i,u} \omega^{sub}_{s,i,u} \qquad \forall s \in SE, \forall u \in U \quad (81)$$

Lembrando que a restrição probabilística (76) está escrita em termos do valor médio da potência aparente e em termos do seu desvio padrão, é possível observar que o valor médio pode ser calculado usando (80); entretanto, a equação quadrática (81) representa o cálculo da variância e não do desvio padrão. Assim, aproveitando que a variância corresponde ao quadrado do desvio padrão, este pode ser obtido através da linearização da equação (81).

Nesse contexto, para linearizar o lado esquerdo da equação (81) propõe-se uma adaptação da função de linearização por partes $f(\rho, \bar{\rho}, \Gamma)$, dado que esta funciona somente para os casos em que se precisa do valor quadrado da variável de interesse. Neste caso, precisa-se da raiz quadrada da variável de interesse. Assim, a nova linearização baseia-se na conhecida linearização por partes acrescentando variáveis binárias junto com novas restrições na formulação original como detalhado a seguir. Essas variáveis binárias são necessárias para ativar cada bloco (parte) de forma sequencial e ordenada desde o valor mínimo até o valor aproximado da variável de interesse.

A linearização proposta calcula a raiz quadrada da variável $\sigma_{s,u}^2$, limitada pelo intervalo $[0, \bar{\sigma}]$, onde $\bar{\sigma}$ representa o máximo desvio padrão. Se o intervalo é particionado em Γ blocos, o conjunto de partições $Q = \{0, \bar{\sigma}/\Gamma, 2\bar{\sigma}/\Gamma, \dots, \bar{\sigma}\}$ deve ser definido tal que cada bloco deveria ter um comprimento de $\bar{\sigma}/\Gamma$. Considerando que $\Delta_{s,\gamma,u}^{\sigma}$ é uma variável continua positiva que define o valor do n-*th* bloco na partição Q, junto com a variável binária $\mathcal{W}_{s,u,\gamma}^{\sigma}$ que define qual bloco do conjunto está ativo, a aproximação linear por partes de $\sigma_{s,u}$ é dada pelo seguinte conjunto de equações (77)–(83).

$$\sum_{\gamma=1}^{\Gamma} m_{s,\gamma,u}^{\sigma} \Delta_{s,\gamma,u}^{\sigma} = \left[\frac{(1+\%P^{loss})}{\phi_{pf}} \right]^2 \sum_i \sigma_{i,u}^{D\,2} \omega_{s,i,u}^{sub} \qquad \forall s \in SE, \forall u \in U \tag{82}$$

$$\sigma_{s,u} = \sum_{\gamma=1}^{\Gamma} \Delta_{s,\gamma,u}^{\sigma} \qquad \forall s \in SE, \forall u \in U \tag{83}$$

$$w_{s,u,\gamma+1}^{\sigma} \le w_{s,u,\gamma}^{\sigma} \qquad \forall s \in SE, \forall u \in U, \ \forall \gamma \in \Gamma / \gamma < \Gamma \tag{84}$$

$$(\bar{\sigma}/\Gamma) \sum_{\gamma=1}^{\Gamma} w_{s,u,\gamma}^{\sigma} \le \sigma_{s,u} \le (\bar{\sigma}/\Gamma)\left(1 + \sum_{\gamma=1}^{\Gamma} w_{s,u,\gamma}^{\sigma}\right) \qquad \forall s \in SE, \forall u \in U \tag{85}$$

$$(\bar{\sigma}/\Gamma) w_{s,u,\gamma}^{\sigma} \le \Delta_{s,\gamma,u}^{\sigma} \qquad \forall s \in SE, \forall u \in U, \tag{86}$$

$$\Delta_{s,\gamma,u}^{\sigma} \le (\bar{\sigma}/\Gamma) w_{s,u,\gamma-1}^{\sigma} \qquad \forall s \in SE, \forall u \in U, \ \forall \gamma \in \Gamma / \gamma > 1 \tag{87}$$

$$\Delta_{s,\gamma,u}^{\sigma} \le (\bar{\sigma}/\Gamma) \qquad \forall s \in SE, \forall u \in U, \ \forall \gamma \in \Gamma / \gamma = 1 \tag{88}$$

A equação (82) representa uma aproximação linear da variança, escrita em termos da declividade do $\gamma - ésimo$ bloco ($m_{\rho,\gamma}$) e do valor da $\gamma - ésima$ variável auxiliar da discretização por partes de $\sigma_{s,u}$ definida como $\Delta^{\sigma}_{s,\gamma,u}$. O desvio padrão é calculado através do sumatorio da variável $\Delta^{\sigma}_{s,\gamma,u}$ como apresentado em (83), enquanto (84) permite que o conjunto de blocos seja ativado de forma sequencial. Os limites mínimo e máximo de $\sigma_{s,u}$ são definidos em (85), enquanto os limites mínimo e máximo de $\Delta^{\sigma}_{s,\gamma,u}$ são definidos por (86)−(88).

Assim, o modelo de PLIM representado pelas equações (1)–(7), (18)–(59), (61), (63)–(68), (76), (78)–(80), (82)–(88), é uma formulação robusta para o problema de PESDM e a alocação e dimensionamento de ECVEs, o qual considera o comportamento estocástico das demandas convencionais e dos VEs. O modelo proposto pode ser resolvido usando técnicas de otimização clássica visando encontrar a solução ótima que garanta o cumprimento da capacidade da subestação com um nível de robustez definido.

5 TESTES E RESULTADOS

Neste capítulo são apresentados os sistemas teste usados para avaliar o desempenho dos modelos matemáticos propostos para resolver o problema de PESDM considerando alocação e dimensionamento de ECVEs e os resultados correspondentes. Os resultados apresentados neste capítulo foram publicados em Banol Arias et al., (2018).

Os modelos matemáticos propostos foram implementados na linguagem de modelamento matemática AMPL (FOURER; GAY; KERNIGHAN, 2003) e resolvidos via CPLEX ("CPLEX Optimization subroutine library guide and reference", 2008). Os testes foram feitos usando um PC com processador Intel core i5-4200 M, CPU 2.50 GHz, 6 GB de Memória RAM e sistema operacional Windows 10 de 64 bits. Foram utilizados dois sistemas teste: Um de 18 nós adaptado do trabalho apresentado em (GÖNEN; RAMIREZ-ROSADO, 1986), e um de 54 nós adaptado dos trabalhos apresentados em Lavorato et al., (2010) e Miranda, Ranito e Proenca, (1994) que serão explicados em detalhe nas próximas subseções.

Nos dois sistemas consideram-se um horizonte de planejamento de 15 anos, dividido em três estágios com uma duração individual de cinco anos cada. A magnitude da tensão mínima é igual a 0,95 pu. O custo das perdas de energia é 0,1 US$/kWh, o fator de perdas ϕ_l é igual a 0,4; a taxa de juros anual é de 10% de acordo com os valores usados em Tabares et al., (2016). Os custos de operação das subestações foram desconsiderados nos testes realizados, i.e., c_s^v igual a zero.

Somente foi considerado um tipo de geração distribuída nos testes realizados com uma capacidade $\left(S_g^{DG}\right)$ igual a 3000 kVA, fator de potência $\left(\phi_g^{dg}\right)$ igual a 0,95 e um custo de investimento $\left(c_g^{edg}\right)$ igual a US$2200/kVA. A alocação de BCs no SDEE é limitada. Assim o número máximo de BCs que podem ser alocados no sistema $(\overline{M})$ é igual a seis, cada um com no máximo quatro módulos $(\overline{N})$. O custo de alocação do BC (c^{cb}) é igual a US$1000 e o custo por módulo (c^{mod}) igual a US$900, com uma potência reativa específica (Q^{cb}) de 300 kVAr.

Os resultados do plano de expansão do SDEE serão analisados considerando um enfoque determinístico e um enfoque robusto. Assim, o modelo proposto será avaliado primeiramente usando valores determinísticos para as demandas, i.e., considerando o correspondente desvio padrão igual a zero. Seguidamente, as incertezas futuras associadas às demandas serão levadas em consideração através da formulação robusta.

5.1 PARÂMETROS DOS VES E DAS ECVES

Nos testes realizados foram considerados dois tipos de veículos para representar a população de VEs: Veículos da marca *Tesla* e *Nissan Leaf* com capacidades de bateria iguais a 50 kWh e 25 kWh, respectivamente. De acordo com o apresentado na seção 3.1, foi assumido um fator conjunto ϕ_{soc} igual a 0,5, que corresponde ao valor médio do SOC inicial dos VEs segundo a função de distribuição de probabilidade apresentada em Quirós-Tortós, Ochoa e Lees (2016).

O nível de penetração dos VEs, ou seja, a porcentagem de usuários de VEs, foi definido como 2%, 11% e 30% para cada estágio do horizonte de planejamento, segundo as informações apresentadas em Frade et al., (2012). Dado que o carregamento dos VEs pode ser feito em zonas residenciais ou em ECVEs públicas, foi assumido que o 20% dos usuários de VEs carregam seus VEs em casa, enquanto o 80% restante carrega seus VEs via ECVEs públicas. Essas porcentagens foram escolhidas aleatoriamente seguindo o próprio critério do autor.

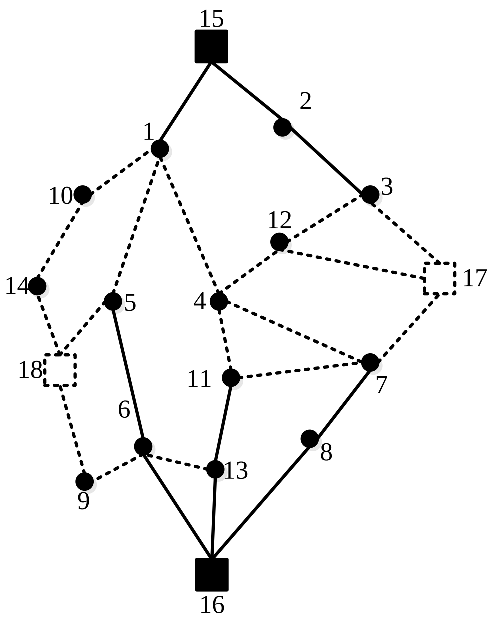
O custo de instalação de uma ECVE foi definido como $c^{cs} = \$500$, incluindo 10% de custo de operação da mesma segundo o apresentado em Cole, (2014). Foi assumido um tempo de operação das ECVEs igual a 12 horas por dia. As ECVEs estarão equipadas com dois tipos de carregadores. Assim, carregadores de nível 2 (comumente conhecidos como carregadores lentos ou *slow charger - SC*) e carregadores de nível 3 (comumente conhecidos como carregadores rápidos ou *fast charger - FC*), foram considerados nos testes. A Tabela 3 apresenta os parâmetros associados aos tipos de carregadores, baseados nas informações apresentadas em Cole (2014 e Tesla Motors (2016).

Tabela 3 – Características dos carregadores das ECVEs.

Tipo	Custo (US$$10^3$)	Potência (kW)
Lentos - SC	9	10
Rápidos - FC	60	50

Fonte: Próprio autor

Figura 4 – Topologia inicial do sistema teste de 18 nós.



Fonte: (BANOL ARIAS et al., 2018)

5.2 SISTEMA TESTE DE 18 NÓS.

O sistema teste de 18 nós possui quatro subestações, 14 nós de carga e 26 circuitos operando a uma tensão nominal de 20 kV. A topologia inicial do sistema é mostrada na Figura 4. O sistema possui inicialmente duas subestações de tipo um, construídas nos nós 15 e 16 no começo do horizonte de planejamento. As subestações construídas estão representadas por quadros pretos e os circuitos construídos estão representados por linhas contínuas, enquanto as subestações e os circuitos para expansão são representados por linhas tracejadas. Os dados das cargas e das linhas do sistema teste encontram-se no Apêndice A.

Dois tipos de alternativas foram considerados para a construção e/ou reforço das subestações com capacidades de 8 MVA e 12 MVA. Da mesma forma, existem dois tipos de condutores para a construção e/ou recondutoramento dos circuitos cujos parâmetros são descritos na Tabela 4, de acordo com as informações apresentadas em (TABARES et al., 2016). Os custos de construção e reforço das subestações e circuitos são mostrados na Tabela 5. Para este sistema, o conjunto de nós candidatos para alocação de GD está conformado pelos nós: {1,3,7,8,9,10,11,12}, considerando um limite de penetração de GD ($\%^{dg}$) de 35% da demanda total do sistema. Além disso, o conjunto de nós candidatos

Tabela 4 – Tipos de alternativas para os circuitos.

Tipo	R_a (Ω / km)	X_a (Ω / km)	$\overline{I}_a$ (A)
1	0,614	0,399	197,00
2	0,307	0,380	314,00

Fonte: Próprio autor

Tabela 5 – Custos de construção e/ou reforço de subestações e circuitos (US$$10^3$).

	Tipo final subestação		Tipo final circuito	
Tipo inicial	1	2	1	2
0 (Não construído)	1000	1800	25	35
1	-	800	-	30

Fonte: (BANOL ARIAS et al., 2018)

para a alocação das ECVEs é composto pelos nós {3,8,9,10,11}. Esses nós devem possuir características adequadas relacionadas ao espaço, serviço e disponibilidade para os moradores próximos, conforme mencionado em (TAYLOR et al., 2009). Por outro lado, assumindo que cada nó do sistema de distribuição atende uma quantidade específica de residências e que existe ao menos um VE por residência, 210, 1688, e 5521 VEs são carregados nas ECVEs durante os três estágios do horizonte de planejamento, respectivamente. Além disso, para os testes de carregamento somente residencial foram considerados carregadores domésticos de nível 1 e 2, com potência nominal igual a 3,6 kW e 10 kW, respetivamente.

5.2.1 PESDM considerando ECVEs: Análise determinística

Nesta subseção apresentam-se os resultados para o problema de PESDM considerando alocação e dimensionamento de ECVE sendo analisado desde um enfoque determinístico. A análise é realizada através da avaliação de dois cenários possíveis:

- Caso A: PESDM sem ECVEs. Neste caso é assumido que todos os VEs são carregados nas residências seguindo o modo de carregamento 2 (ver seção 2.2.3). Além disso, é assumido que esses VEs são carregados na hora pico, visando representar o pior caso para a operação do SDEE.

- Caso B: PESDM com ECVEs. Neste caso é assumido que o carregamento dos VEs é dividido em duas parcelas, em que uma parcela é carregada em casa (sendo realizado na hora pico, mesmo que no caso anterior) e outra parcela é carregada em ECVEs públicas. Nesse contexto, o problema de PESDM é resolvido considerando alocação e dimensionamento de ECVEs.

Os resultados dos custos totais do plano de expansão para cada caso são apresentados na Tabela 6. Nessa tabela pode ser observado que a consideração das ECVEs como meio para suprir energia aos VEs causa um impacto positivo sobre o SDEE. Quando a demanda associada aos VEs é distribuída em cada nó do SDEE (Caso A), a demanda convencional aumenta provocando a realização de investimentos adicionais para atender toda a demanda. É por este motivo que o Caso A apresenta custo maior em subestações, circuitos e unidades de GD, assim como também no custo da energia suprida pelas subestações e as unidades de GD durante todo o horizonte de planejamento.

No caso B, onde a demanda associada aos VEs é concentrada em alguns nós do SDEE (i.e., carregamento de VEs em ECVEs), os custos de investimento do plano de expansão são reduzidos em 3,12% aproximadamente, causando um impacto positivo para o SDEE quando comparado com o caso A. Os planos de expansão para ambos os casos são mostrados na Figura 5 e na Figura 6.

Dado que o modelo proposto considera a reconfiguração da rede, a Figura 5 e a Figura 6 mostram a topologia em operação da rede de distribuição. Note-se que sem ECVEs (Figura 5), foram construídas duas subestações nos nós 17 e 18 no estágio três do horizonte de planejamento. Além disso, a maioria dos circuitos foram construídos com os condutores de maior capacidade (linhas verdes representam os condutores de tipo 1 e as azuis os de tipo 2).

No caso B, quando as ECVEs são consideradas, a topologia da rede é diferente. Somente a subestação do nó 17 foi construída no estágio três, e diferentes circuitos foram construídos e/ou recondutorados usando a maioria das vezes, condutores de menor capacidade como mostrado na Figura 6.

Tabela 6 – Custos totais do plano de expansão (US\$$10^3$): Análise determinística.

Tipo de custo	Caso A	Caso B
IS	1006,46	385,54
IC	397,74	355,32
IBC	21,74	23,39
IGD	7462,42	5766,03
IECV	0	2324,73
CES	55686,72	49163,03
CEGD	11424,7	9155,88
Custo total	75999,78	67173,92

Fonte: (BANOL ARIAS et al., 2018)

Figura 5 – Plano de expansão para o Caso A.

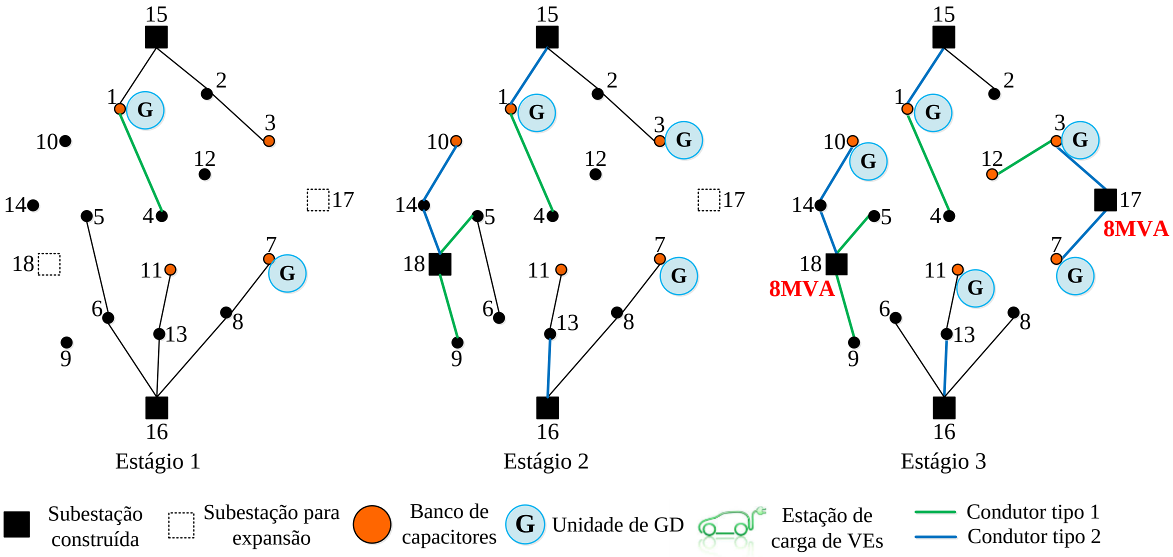
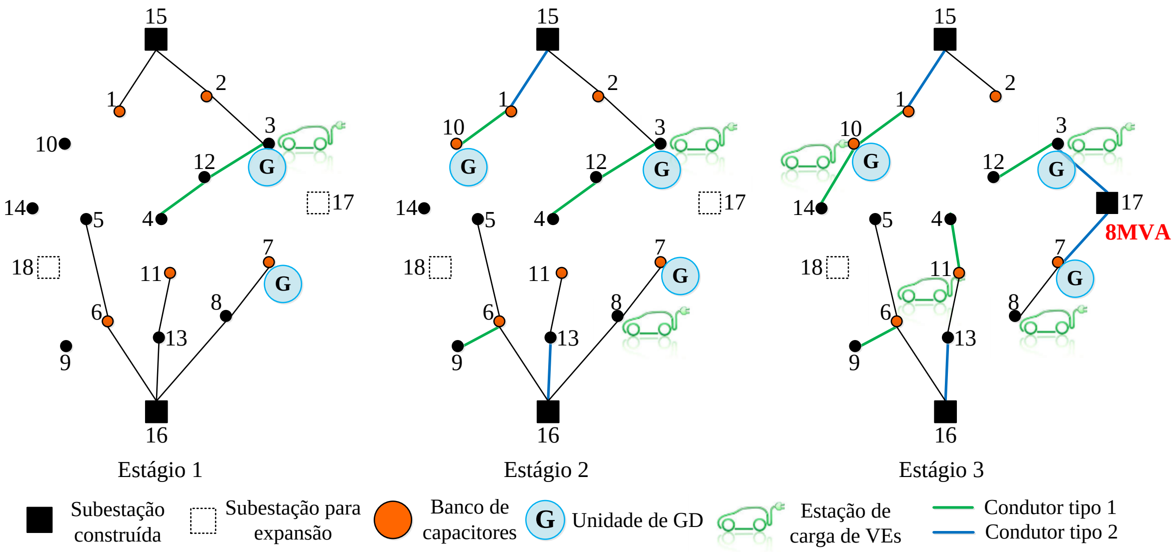


Figura 6 – Plano de expansão para o Caso B.



Fonte: (BANOL ARIAS et al., 2018)

Além disso, a alocação das unidades de GD (representada pelo círculo azul) e os BCs (representado pelos pontos laranja) também foram diferentes quando as ECVEs são consideradas no planejamento da expansão. No caso B somente três unidades de GD foram instaladas no estágio três, enquanto no Caso A cinco unidades de GD foram requeridas no mesmo estágio.

As ECVEs (representadas pelos carros verdes) foram principalmente alocadas nos nós próximos às unidades de GD e os BCs, na tentativa de manter uma operação adequada do SDEE. Por exemplo, uma ECVE foi alocada no nó três junto com uma unidade de GD no estágio um, e outra ECVE junto com um BC foi alocada no nó 11 no estágio três.

As informações relacionadas com as ECVEs são mostradas na Tabela 7. No caso B foram requeridas um total de quatro ECVEs e 277 carregadores, equipadas com 47 FCs e 230 SCs para atender a demanda de potência dos VEs durante o horizonte de planejamento.

Outro ponto importante foi que em ambos os casos, alguns circuitos foram desconectados visando manter a operação radial do SDEE.

Tabela 7 – Número de ECVEs e carregadores: Análise determinística.

Estágio	1		2		3	
Nó	FC	SC	FC	SC	FC	SC
3	2	9	14	7	23	187
8	-	-	7	1	-	-
14	-	-	-	-	1	3
15	-	-	-	-	-	23
Total	2	9	21	8	24	213

Fonte: (BANOL ARIAS et al., 2018)

5.2.2 PESDM considerando ECVEs: Análise robusta

Nesta subseção apresentam-se os resultados para o problema de PESDM considerando alocação e dimensionamento de ECVEs, analisado desde um enfoque robusto. A análise é realizada através da extensão do Caso B apresentado na subseção anterior, com a diferença de que para este caso, as demandas convencionais e o número de VEs são considerados parâmetros estocásticos. Assim o problema é resolvido usando a formulação robusta proposta na seção 4.1.2.

- Caso C: PESDM com ECVEs. Da mesma forma que para o Caso B, é assumido que o carregamento dos VEs é dividido em duas parcelas, em que a primeira é carregada nas residências (sendo realizado na hora pico, mesmo que no caso anterior) e a segunda é carregada em ECVEs públicas. Porém, neste caso, é considerado que as demandas convencionais e o número de VEs são desconhecidos (incertos).

Para a realização desta análise foi assumido que as demandas convencionais e o número de VEs seguem uma distribuição normal. Os valores médios das demandas convencionais correspondem aos valores de demanda relacionados nos dados do sistema teste (ver Apêndice A), enquanto os valores médios do número de VEs são os mesmos apresentados na Seção 5.2. Além disso, foi assumido um desvio padrão de 15% dos valores médios correspondentes à demanda convencional e o número de VEs presentes no sistema.

O parâmetro robusto usado nas restrições probabilísticas para a capacidade da subestação e a estimação do número de VEs foi igual a 5%. Assim o valor de $\phi(\varepsilon)$ é igual a 1,645. Este valor garante o cumprimento da restrição da capacidade da subestação com um 95% de probabilidade. Do mesmo modo, este parâmetro também cobre 95% da área abaixo da curva de distribuição normal para a penetração dos VEs.

Os resultados dos custos de investimento do plano de expansão para o Caso B e o Caso C são apresentados na Tabela 8. Nesta tabela são incluídos novamente os resultados do Caso B visando fazer uma análise comparativa entre o enfoque determinístico e o enfoque robusto.

Na Tabela 8 pode ser observado que o custo total do plano de expansão considerando um enfoque robusto é maior do que o custo total do plano de expansão do enfoque determinístico em aproximadamente 4%. O principal motivo dessde aumento deve-se aos investimentos adicionais requeridos para garantir uma capacidade suficiente nas subestações, levando em consideração a natureza incerta das demandas.

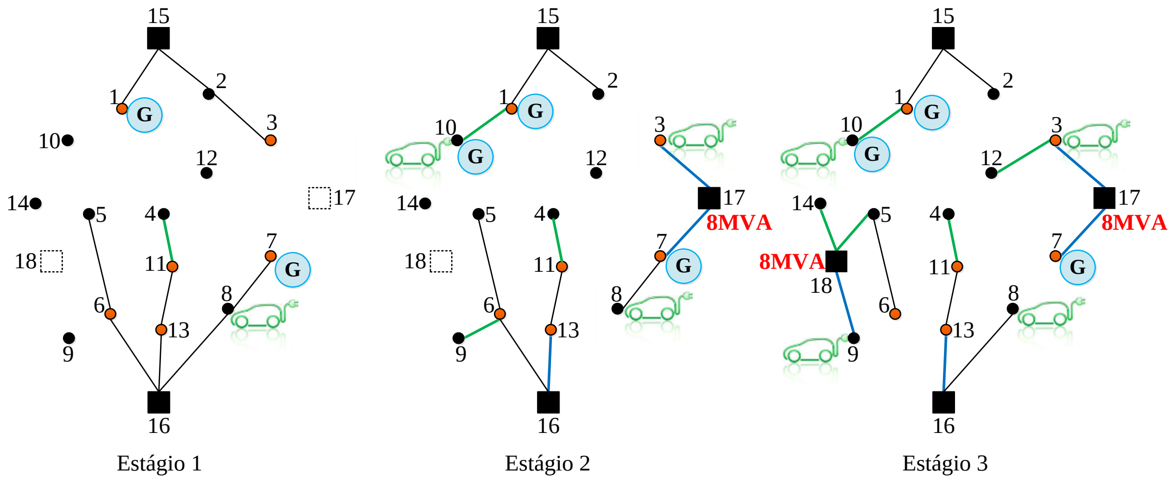
A Figura 7 mostra os planos de expansão em cada estágio para o caso C. Note que duas novas subestações foram construídas durante o horizonte de planejamento. As subestações 17 e 18 foram construídas nos estágios dois e três, respectivamente. Em comparação com o Caso B, deve-se ressaltar que uma subestação adicional foi requerida,

Tabela 8 – Custos totais do plano de expansão (US$$10^3$): Análise robusta.

Tipo de custo	Caso B	Caso C
IS	385,54	1006,46
IC	355,32	339,11
IBC	23,39	24,22
IGD	5766,03	5766,03
IECV	2324,73	2875,22
CES	49163,03	50170,36
CEGD	9155,88	9155,88
Custo total	67173,92	69337,28

Fonte: (BANOL ARIAS et al., 2018)

Figura 7 – Plano de expansão Caso C.



Fonte: (BANOL ARIAS et al., 2018)

visando evitar possíveis sobrecargas relacionadas ao crescimento de demanda, o qual pode ser maior do que o esperado. Note-se também que os investimentos nos circuitos e a topologia da rede de distribuição foram diferentes quando comparados com o Caso B. Assim, circuitos de maior capacidade (tipo 2) foram usados principalmente para conectar as ECVEs.

A alocação das unidades de GD e dos BCs ao longo do horizonte de planejamento foi diferente também se comparado com o Caso B. Apesar do número de unidades de GDs ser igual em ambos os casos, a alocação é diferente. No caso B, três unidades de GD foram usadas e alocadas nos nós 3, 7 e 10, enquanto no caso C foram usadas e alocadas nos nós 1, 7 e 10, no último estágio de planejamento.

Tabela 9 – Número de ECVEs e carregadores: Análise robusta.

Estágio	1		2		3	
Nó	FC	SC	FC	SC	FC	SC
3	-	-	6	-	-	52
8	3	8	2	-	16	41
14	-	-	-	-	3	214
15	-	-	20	1	2	6
Total	3	8	28	1	21	313

Fonte: (BANOL ARIAS et al., 2018)

As informações relacionadas com a alocação e o dimensionamento das ECVEs são apresentadas na Tabela 9. Note que no Caso C foram requeridas um total de quatro ECVEs e 374 carregadores, equipadas com 52 FCs e 322 SCs para atender a demanda de potência dos VEs durante o horizonte de planejamento. Assim como no Caso B, a maioria das ECVEs foram alocadas em nós próximos a fontes de energia e BCs.

Os resultados mostram que os planos de expansão para os enfoques determinístico e robusto (Caso B e C, respectivamente) foram diferentes em termos dos custos de investimento nas subestações, circuitos, BCs e ECVEs. Esses custos foram acrescentados visando fornecer uma solução suficientemente robusta para o problema de PESDM.

Em todos os casos os resultados mostraram mudanças na topologia da rede, no recondutoramento de circuitos e na construção de novas subestações. Esses investimentos foram realizados visando atender os requisitos de potência tanto da demanda convencional como da demanda associada aos VEs.

Na Tabela 10 apresenta-se o tempo computacional necessário para encontrar a solução em cada um dos casos simulados junto com o *Gap* de otimilidade, que é uma medição comumente usada na solução de modelos matemáticos para indicar a qualidade da solução encontrada em comparação com a solução ótima do problema.

Tabela 10 – Resumo dos tempos computacionais.

Caso	Tempo de processamento (s)	*Gap* de otimalidade (%)
A	4071,19	0
B	30522,0	0,05
C	31602,2	0,03

Fonte: Próprio autor

5.2.2.1 Simulações de Monte Carlo

Nesta subseção apresentam-se os resultados obtidos após a aplicação da técnica de simulações de Monte Carlo (SMC) com o objetivo de avaliar a robustez da formulação proposta neste trabalho (enfoque robusto). A SMC é uma técnica tradicional que permite a construção de uma função de distribuição através da geração de parâmetros de entrada aleatórios (SANKARAKRISHNAN; BILLINTON, 1995). A robustez da formulação proposta é avaliada através do cálculo do cumprimento da equação (55), desenvolvida para as ECVEs, e da restrição probabilística (75), desenvolvida para a capacidade da subestação. Essa condição é representada através de uma taxa de falhas que indica em forma de porcentagem, o número de vezes em que cada restrição foi infringida após um determinado número de SMC.

As SMC para calcular a taxa de falhas da capacidade das subestações e das ECVEs foram realizadas seguindo o processo heurístico descrito a seguir:

1) *Definir os parâmetros de entrada: Número total de SMC, função de distribuição de probabilidade para a demanda convencional e o número de VEs;*
2) *Inicializar em zero os contadores de cumprimento da capacidade da subestação (cont_S) e da capacidade das ECVEs (cont_ECVE);*
3) *Fixar a solução do modelo matemático obtida para cada Caso (B ou C), ou seja, investimentos em subestações, circuitos, BCs, unidades de GD, estações de carregamento de VEs e topologia da rede;*
4) *Gerar um valor aleatório de demanda para cada nó do sistema e para o número de VEs presentes no sistema, seguindo a função de distribuição de probabilidade definida no passo 1;*
5) *Resolver o modelo matemático para obter as variáveis de operação $P_{s,u}^{S}$ e $Q_{s,u,}^{S}$ e calcular o valor de $S_{s,u}^{S}$ através da equação (13) e para obter o valor da variável $C_{m,u}^{VE}$[1];*
6) *Verificar se o valor de $S_{s,u}^{S}$ calculado no passo anterior satisfaz a restrição (14), cujo equivalente probabilístico corresponde à restrição (75). Se (14) é satisfeita,*

[1] Como a equação (55) é uma expressão de igualdade, foi necessário adicionar no lado esquerdo da equação, um termo de corte de VEs ($C_{m,u}^{VE}$) que indica quantos VEs ficam desatendidos em cada simulação. Se $C_{m,u}^{VE}$ é igual a zero, significa que as ECVEs foram suficientes para atender a demanda dos VEs. No entanto, se $C_{m,u}^{VE}$ é diferente de zero, significa que as ECVEs não foram suficientes, e alguns VEs não conseguiram ser atendidos.

o cont_S é igual a zero, caso contrário o cont_S é igual a 1. Por outro lado, se $C_{m,u}^{VE}$ é igual a zero o cont_ECVE é igual a zero. Porém, se $C_{m,u}^{VE}$ é diferente de zero, o cont_ECVE é igual a 1. Ambos os contadores devem ser acumulados em cada iteração das SMC;

7) *Voltar ao passo 4 e repetir até atingir o número máximo de SMC;*
8) *Calcular a taxa de falhas para a capacidade da subestação através da equação: 100* cont_S/# de SMC, e para a capacidade das ECVEs através da equação: 100* cont_ECVE/# de SMC.*

As SMC foram realizadas levando em consideração a distribuição normal da demanda estocástica e do número de VEs. Assim, dado que a distribuição normal precisa dos valores médios e do desvio padrão de cada uma das variáveis, os valores médios das demandas convencionais foram assumidos como os valores nominais de demanda relacionados nos dados do sistema teste (ver Apêndice A). Os valores médios do número de VEs foram assumidos como os valores nominais apresentados na Seção 5.2. Alem disso, o desvio padrão foi assumido como um 15% dos valores médios correspondentes à demanda convencional e do número de VEs presentes no sistema.

A Tabela 11 mostra a taxa de falhas da capacidade da subestação para os casos B e C em cada estágio do horizonte de planejamento. Os resultados obtidos após 1000 SMC mostraram que o enfoque determinístico (Caso B) apresenta o pior desempenho com violações nas capacidades da subestação maiores que 10%. O pior caso corresponde à subestação do nó 16 onde a violação é maior que 65% no estágio dois. Assim, apesar do plano de expansão do Caso C ser mais caro, a taxa de falhas da capacidade da subestação é mantida dentro do limite definido pelo parâmetro robusto, i.e., menor que 5%.

A Tabela 12 mostra a taxa de falhas das ECVEs para os casos B e C em cada estágio do horizonte de planejamento. Note-se que novamente o Caso B apresenta o pior desempenho com taxas de falha nas ECVEs maiores que 35% em todos os estágios do horizonte de planejamento. O Caso C pelo contrário, mostra taxas de falhas menores que 1,5% mantendo-se dentro do limite definido pelo parâmetro robusto, i.e., menor que 5%.

Tabela 11 – Taxa de falhas na capacidade das subestações (%).

	Estágio 1				Estágio 2				Estágio 3			
Subestação	15	16	17	18	15	16	17	18	15	16	17	18
Caso B	0,0	0,2	-	-	3,9	67,9	-	-	43,8	36,6	0,4	-
Caso C	0,0	1,4	-	-	0,0	0,0	0,2	-	0,0	2,6	2,2	1,0

Fonte: (BANOL ARIAS et al., 2018a)

Tabela 12 – Taxa de falhas das ECVEs (%).

Estágio	1	2	3
Caso B	36,9	47,8	49,1
Caso C	0,5	1,2	1,4

Fonte: Próprio autor

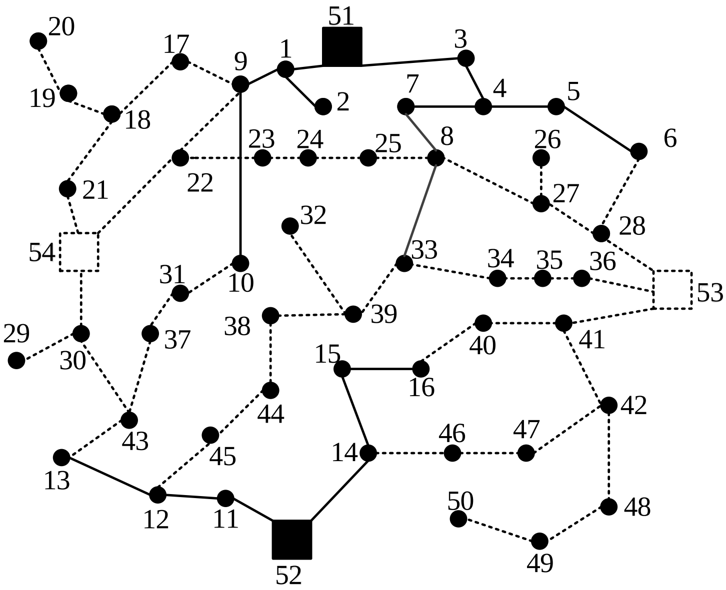
5.3 SISTEMA TESTE DE 54 NÓS

Nesta seção apresentam-se os resultados para o sistema teste de 54 nós, visando verificar a escalabilidade do modelo proposto. Consideram-se os mesmos cenários descritos nas seções 5.2.1 e 5.2.2 para o sistema de 18 nós. O sistema teste de 54 nós possui quatro subestações, 50 nós de carga e 61 circuitos operando a uma tensão nominal de 15 kV. A topologia inicial do sistema é mostrada na Figura 8. O sistema possui inicialmente duas subestações de tipo um, construídas nos nós 51 e 52 no começo do horizonte de planejamento. As subestações e linhas construídas e por construir seguem o mesmo esquema de representação do sistema de 18 nós apresentado na seção anterior. Os dados das cargas e das linhas do sistema teste encontram-se no Apêndice B deste trabalho.

Dois tipos de alternativas foram considerados para a construção e/ou reforço das subestações com capacidades de 22 MVA e 32 MVA, e um tipo de condutor foi considerado para a construção e/ou recondutoramento dos circuitos cujos parâmetros são descritos na Tabela 13. Os custos de construção e reforço das subestações e circuitos são mostrados na Tabela 14.

Para este sistema, o conjunto de nós candidatos para alocação de GD é definido pelos nós: {5,7,8,10,12,13,15,16,17,19,20,23,24,26,27,29,31,32,34,35,37,39,40,42,43,45,46,49,50}, considerando um limite de penetração de GD ($\%^{dg}$) de 35% da demanda total do sistema. Além disso, o conjunto de nós candidatos para a alocação das ECVEs é composto pelos nós

Figura 8 – Topologia inicial do sistema teste de 54 nós.



Fonte: Próprio autor

Tabela 13 – Tipos de alternativas para os circuitos.

Tipo	R_a (Ω / km)	X_a (Ω / km)	$\bar{I}_a$ (A)
1	0,0966	0,1140	600,00

Fonte: Própio autor

Tabela 14 – Custos de construção e/ou reforço de subestações e circuitos (US\$$10^3$).

	Tipo final subestação		Tipo final
Tipo inicial	1	2	1
0 (Não construído)	1000	2500	90
1	-	1300	-

Fonte: Próprio autor

{13,20,22,26,29,32,33,39,42,50}. O número de VEs que devem ser carregados em ECVEs corresponde a 278, 2084, e 7128 durante os três estágios do horizonte de planejamento, respectivamente, considerando somente um tipo de VE e a mesma base de cálculo apresentada na seção 5.2.

Tabela 15 – Custos totais do plano de expansão (US$$10^3$): Análise determinística.

Tipo de custo	Caso A	Caso B
IS	3503,62	1000,00
IC	6507,71	6538,55
IBC	25,86	20,39
IGD	18160,5	10166,03
IECV	0	3348,01
CES	71483,09	53231,52
CEGD	12770,85	8852,22
Custo total	112451,63	83156,72

Fonte: Próprio autor

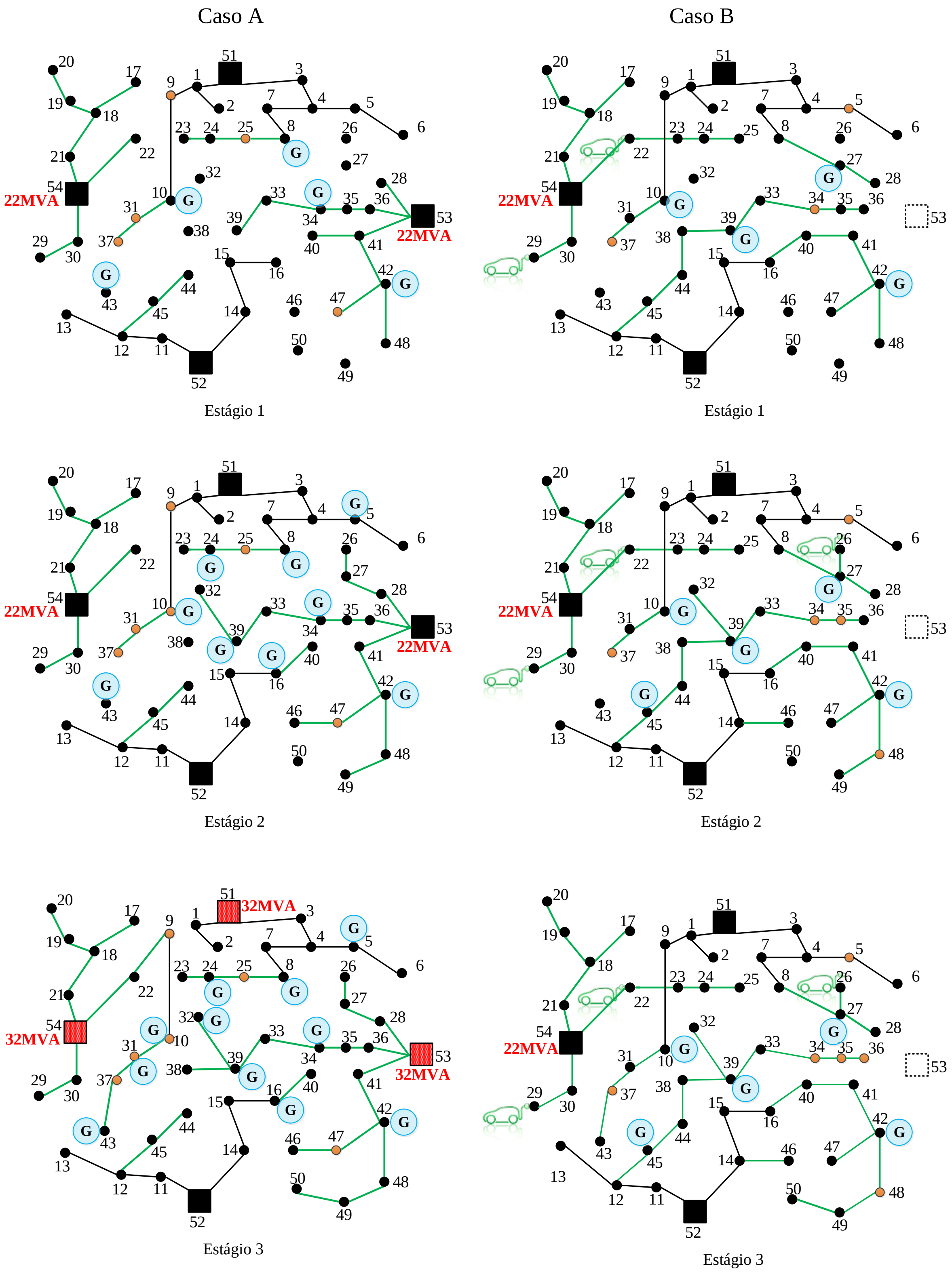
5.3.1 PESDM considerando ECVEs: Análise determinística

Os resultados dos custos totais do plano de expansão para cada caso são apresentados na Tabela 15. Novamente pode ser observado que a consideração das ECVEs como meio para suprir a energia aos VEs causa um impacto positivo sobre o SDEE. Quando a demanda associada aos VEs é distribuída em cada nó do SDEE (Caso A), a demanda convencional aumenta provocando a realização de investimentos adicionais. É por este motivo que o Caso A apresenta custo maior em subestações, circuitos e unidades de GD, assim como também no custo da energia suprida pelas subestações e as unidades de GD durante todo o horizonte de planejamento.

No caso B, onde a demanda associada aos VEs é concentrada em alguns nós do SDEE, os custos de investimento do plano de expansão são reduzidos em 26% aproximadamente, o qual demonstra a grande vantagem de considerar ECVEs para atender a demanda de energia dos VEs.

Os planos de expansão para ambos os casos são mostrados na Figura 9, correspondendo à topologia em operação do sistema dado que o modelo proposto considera reconfiguração da rede. Note-se que sem ECVEs (Caso A) foram construídas todas as subestações desde o primeiro estágio do horizonte de planejamento. Logo depois, as subestações alocadas nos nós 51, 53 e 54 foram reforçadas no estágio três enquanto no caso B, somente a subestação do nó 54 foi construída no mesmo estágio. Em ambos os casos, os circuitos foram construídos com um tipo de condutor, dado que somente foi considerada uma única opção para sua construção.

Figura 9 – Planos de expansão para os Casos A e B.



Fonte: Próprio autor

A topologia das redes em ambos os casos é também diferente. No caso A, por exemplo, os circuitos 25-8, 53-28, 53-36, 53-41 foram construídos e mantidos durante o horizonte de planejamento. No caso B, esses circuitos não foram construídos, porém, outros foram utilizados como o caso das linhas 22-23 e 38-44.

Na Figura 9 é também possível observar que a alocação das unidades de GD (representada pelo círculo azul) e os BCs (representado pelos pontos laranja) é diferente em ambos os casos. No caso B cinco unidades de GD foram instaladas no estágio três, enquanto no Caso A foram necessárias onze unidades no mesmo estágio. Em relação aos BCs, no caso B foram instalados cinco em quanto no caso A foram instalados seis. Vale a pena mencionar que os BCs foram alocados principalmente em nós finais, afastados das subestações, onde usualmente são observados problemas de queda de tensão.

De forma similar aos resultados encontrados para o sistema de 18 nós, no caso B, as ECVEs foram principalmente alocadas em nós próximos a fontes geradoras como são as subestações e as unidades de GD, na tentativa de manter uma operação adequada do SDEE. A alocação e dimensionamento das ECVEs são mostradas na Tabela 16. Em total foram requeridas três ECVEs equipadas com 792 carregadores lentos (SCs) para atender a demanda dos VEs durante o horizonte de planejamento.

Tabela 16 – Número de ECVEs e carregadores: Análise determinística.

Estágio	1		2		3	
Nó	FC	SC	FC	SC	FC	SC
22	-	24	-	58	-	381
26	-	-	-	75	-	-
29	-	7	-	68	-	179
Total	0	31	0	201	0	560

Fonte: Próprio autor

5.3.2 PESDM considerando ECVEs: Análise robusta

Da mesma forma que considerado na seção de resultados da análise robusta para o sistema teste de 18 nós (Seção 5.2.2), na realização desta análise assume-se que as demandas convencionais e o número de VEs seguem uma distribuição normal. Os valores médios das demandas convencionais correspondem aos valores de demanda relacionados nos dados do sistema teste (ver Apêndice B), enquanto os valores médios do número de VEs são os mesmos apresentados na seção 5.3. Além disso, foi assumido um

Tabela 17 – Custos totais do plano de expansão (US$$10^3$): Análise robusta.

Tipo de custo	Caso B	Caso C
IS	1000,00	1385,54
IC	6538,55	7117,93
IBC	20,39	18,91
IGD	10166,03	13732,05
IECV	3348,01	4188,81
CES	53231,52	52733,1
CEGD	8852,22	9492,25
Custo total	83156,72	88668,59

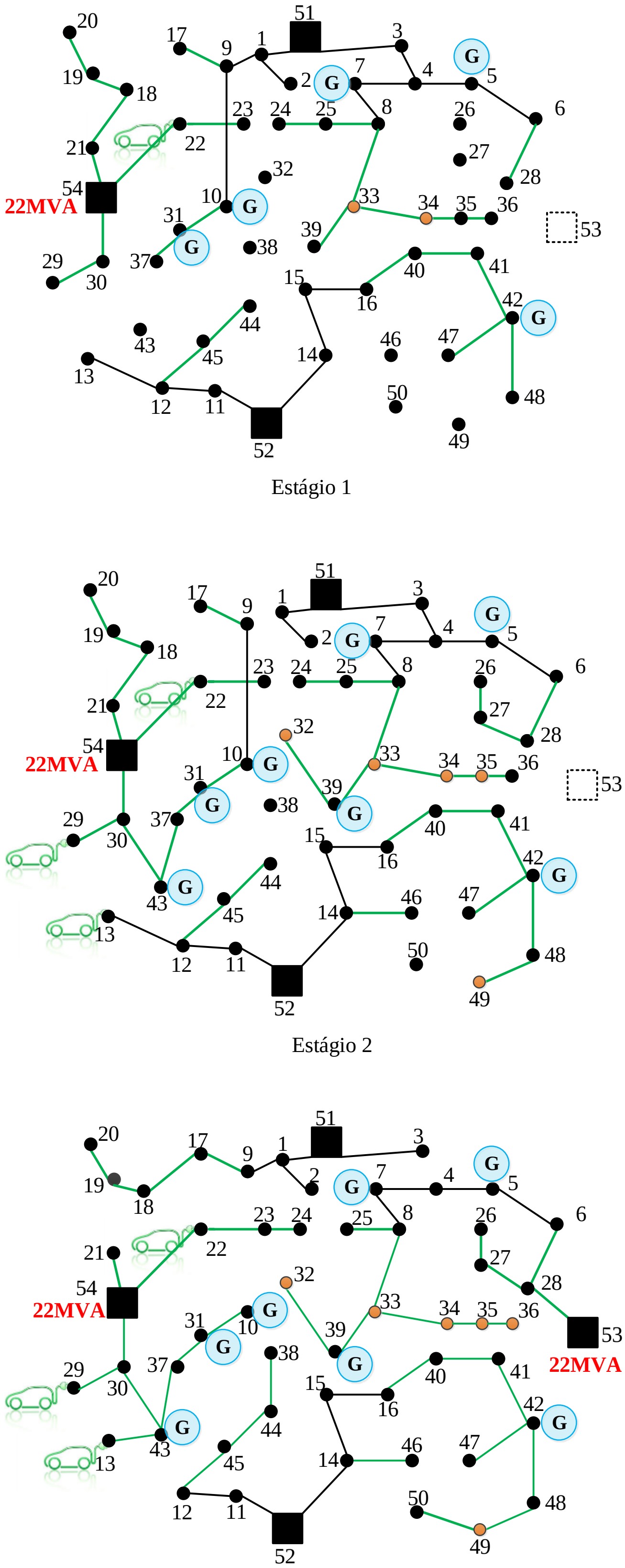
Fonte: Próprio autor

desvio padrão de 15% dos valores médios correspondentes à demanda convencional e o número de VEs presentes no sistema. O parâmetro robusto usado nas restrições probabilísticas para a capacidade da subestação e a estimação do número de VEs foi igual a 5% que corresponde a um valor igual a 1,645 para $\phi(\varepsilon)$. Os resultados são analisados considerando os mesmos cenários (Caso B e Caso C) descritos nas seções 5.2.1 e 5.2.2.

Os resultados dos custos de investimento do plano de expansão para o Caso B e o Caso C são apresentados na Tabela 17 mostrando resultados similares aos resultados obtidos para o sistema de 18 nós. O custo total do plano de expansão sob o enfoque robusto é maior do que o custo total sob o enfoque determinístico em aproximadamente 6%. Esse aumento deve-se aos investimentos adicionais requeridos para se proteger contra as incertezas associadas as demandas e garantir uma capacidade suficiente das subestações.

A Figura 10 mostra os planos de expansão em cada estágio para o caso C. Note que duas novas subestações nos nós 53 e 54 foram construídas nos estágios dois e três, respectivamente. Comparando com os resultados do caso B, uma subestação adicional foi requerida visando evitar possíveis sobrecargas relacionadas ao crescimento da demanda. Além disso, os investimentos nos circuitos e a topologia da rede de distribuição foram diferentes. A alocação das unidades de GD ao longo do horizonte de planejamento também foi diferente quando comparado com o Caso B. No caso C, sete unidades de GD foram instaladas, enquanto no caso B somente 5 unidades foram instaladas. Em relação aos BCs, em ambos os casos foram alocados seis BCs, apresentando uma pequena diferença no número de módulos instalados. Isso explica a diferença entre os custos de investimento desses equipamentos.

Figura 10 – Plano de expansão para o Caso C.



Estágio 1

Estágio 2

Estágio 3

Fonte: Próprio autor

Tabela 18 – Número de ECVEs e carregadores: Análise robusta.

Estágio	1		2		3	
Nó	FC	SC	FC	SC	FC	SC
13	-	-	1	-	-	-
22	-	39	1	164	-	469
29	-	-	-	75	-	230
Total	0	39	2	239	0	699

Fonte: Próprio autor

Tabela 19 – Resumo dos tempos computacionais.

Caso	Tempo de processamento (s)	Gap de optimalidade (%)
A	2277,52	0,01
B	20217,24	0,03
C	24338,99	0,03

Fonte: Próprio autor

As informações relacionadas com alocação e o dimensionamento das ECVEs são apresentadas na Tabela 18. Note que no Caso C foram requeridas em total três ECVEs para atender a demanda de potência dos VEs durante o horizonte de planejamento. Em total foram instalados 979 carregadores dos quais 2 foram FCs e 977 foram SCs. Mesmo que no sistema teste anterior, a maioria das ECVEs foram alocadas em nós próximos a fontes de energia e BCs.

Os resultados mostraram que os planos de expansão para os enfoques determinístico e robusto (Caso B e C, respectivamente) foram diferentes em termos dos custos de investimento nas subestações, circuitos, BCs e ECVEs. Esses custos foram acrescentados visando fornecer uma solução suficientemente robusta para o problema de PESDM.

Por outro lado, a Tabela 19 apresenta o tempo computacional necessário para encontrar a solução em cada um dos casos simulados.

5.3.2.1 Simulações de Monte Carlo

Nesta subseção verifica-se o cumprimento da equação (55) desenvolvida para as ECVEs e da restrição probabilística (75), desenvolvida para a capacidade da subestação através de SMC, com o objetivo de avaliar a robustez da formulação proposta para o sistema de 54 nós. Mesmo que para o sistema de 18 nós, as SMC foram realizadas considerando uma distribuição normal da demanda estocástica e do número de VEs. A Tabela 20 mostra a taxa de falhas da capacidade da subestação para os casos B e C em cada estágio do horizonte de planejamento. Os resultados obtidos após 1000 SMC mostraram que o enfoque determinístico (Caso B) apresenta poucos casos com violações nas capacidades da subestação. O pior e único caso corresponde à subestação do nó 51 onde a violação é aproximadamente 19% no estágio três. No Caso C, apesar do plano de expansão ser mais caro, a taxa de falhas da capacidade da subestação é mantida dentro do limite permitido (i.e., menor que 5%).

A taxa de falhas das ECVEs foi verificada usando a sub-rotina descrita na seção 5.2.2.1. A Tabela 21 mostra a taxa de falhas das ECVEs para os casos B e C em cada estágio do horizonte de planejamento. Note-se que novamente o Caso B apresenta o pior desempenho com taxas de falha nas ECVEs maiores que 47% em todos os estágios do horizonte de planejamento. Contrariamente, o Caso C mostra taxas de falhas mantidas dentro do limite definido pelo parâmetro robusto, i.e., menor que 5%.

5.4 CONSIDERAÇÕES FINAIS

Os resultados obtidos permitem observar o impacto da demanda associada aos VEs elétricos no planejamento da expansão do SDEE. É claro que o incremento da demanda convencional em cada nó do sistema resulta em planos de expansão mais custosos. Porém, resulta vantajoso para o OSD atender uma demanda (associada aos VEs) concentrada em alguns pontos da rede de distribuição. Assim, independentemente de se as ECVEs são propriedade do OSD ou pertencem a empresas privadas, é claro que desde o ponto de vista do SDEE o carregamento dos VEs em ECVEs favorece a operação do sistema. Isso abre passo à criação de novos modelos de negócio onde novos desafios devem ser enfrentados, principalmente aqueles relacionados com a interação entre as partes interessadas, (OSDs, empresas privadas proprietárias das ECVEs, consumidores finais, etc) as regulamentações de mercado, desenvolvimentos tecnológicos e plataformas de comunicação, as quais habilitem a participação ativa de todas as partes envolvidas. A consideração da interação desses novos entes dentro do problema de PESDM pode resultar em planos de expansão totalmente diferentes.

Tabela 20 – Taxa de falhas na capacidade das subestações (%).

	Estágio 1				Estágio 2				Estágio 3			
Subestação	51	52	53	54	51	52	53	54	51	52	53	54
Caso B	0,0	0,0	-	0,0	0,0	0,0	-	0,0	18,9	0,0	-	1,5
Caso C	0,0	0,0	-	0,0	0,0	0,0	-	0,0	0,0	0,0	0,0	0,1

Fonte: Próprio autor

Tabela 21 – Taxa de falhas das ECVEs (%).

Estágio	1	2	3
Caso B	47,3	49,9	48,4
Caso C	3,6	4,6	3,8

Fonte: Próprio autor

Por outro lado, os resultados mostram que em termos de economia, o melhor plano de investimento é fornecido pelo enfoque determinístico, ou seja, o Caso B. Porém, sob condições de demanda convencional e uma taxa de crescimento da penetração dos VEs incerta, o plano de expansão poderia ser infactível em muitos cenários. O plano de investimento fornecido pelo enfoque estocástico (Caso C) é suficientemente robusto para lidar com a incerteza associada às variáveis de demanda. No entanto, este plano apresenta um custo de investimento maior.

6 CONCLUSÕES E TRABALHOS FUTUROS

Neste trabalho foi apresentada uma proposta para abordar e resolver o problema de PESDM considerando a integração de VEs. Este problema, que é naturalmente um problema de PNLIM, foi reformulado como um problema de PLIM através de técnicas de linearização. Para considerar as incertezas associadas à demanda convencional e dos VEs, esse modelo foi estendido para uma formulação robusta através de restrições probabilísticas. Dois sistemas de distribuição foram usados para avaliar a eficiência do método proposto. Neste capítulo, apresentam-se as conclusões e sugestões de futuras pesquisas.

6.1 CONCLUSÕES

- O problema de PESDM foi resolvido usando um modelo de PLIM considerando o impacto das ECVEs. A formulação proposta define a construção de novas subestações, ECVEs e circuitos e/ou o reforço de subestações, ECVE e circuitos já existentes. Define também a alocação de unidades de GD e BCs. Além disso, a formulação proposta é robusta devido à consideração das incertezas associadas à demanda convencional e dos VEs. Um método baseado em programação com restrições probabilísticas foi desenvolvido para garantir os limites de capacidade da subestação e os requerimentos dos VEs com um determinado nível de confiança.

- Foi demonstrado que o SDEE é afetado pela integração de VEs no sistema. O impacto é principalmente refletido pelas diferenças entre os investimentos realizados em subestações e circuitos, assim como também a topologia da rede. Além disso, pela redução do custo total do plano de investimento quando as ECVEs são consideradas no plano de expansão. Deste modo, pode ser concluído que para os OSDs resulta mais interessante atender a carga agregada dos VEs através de ECVEs, já que um incremento da carga espalhado em toda a rede de distribuição requer uma maior expansão da rede.

- Por outro lado, foi encontrado que através de um enfoque determinístico é possível obter um plano de expansão mais atrativo em termos econômicos. No entanto, sob os ambientes incertos de demanda convencional e de penetração de VEs, o plano de expansão poderia apresentar uma alta taxa de falhas para a capacidade da subestação. Pelo contrário, a solução robusta fornece um plano de expansão com um custo maior, porém, suficientemente robusto para lidar com as incertezas associadas à demanda. Desta forma, o tomador de decisões tem várias alternativas e pode escolher o plano de expansão de acordo com o nível de risco que esteja disposto a assumir, associado às variações de demanda na operação do SDEE.

- Os resultados mostraram que uma alta penetração de VEs impacta significativamente a operação do SDEE, independentemente do ponto de conexão. Portanto, os OSDs devem estar preparados de forma apropriada para uma penetração massiva de VEs já que em um cenário futuro, é esperado que este serviço seja ofererecido também por empresas privadas provocando novos desafios e mudanças na operação e expansão da rede.

6.2 TRABALHOS FUTUROS

Os resultados obtidos neste trabalho revelaram possíveis tópicos que ainda podem ser explorados, os quais são descritos a seguir:

1. Como foi descrito no Capítulo 3, a operação das ECVEs depende de informações altamente incertas, por exemplo, o estado inicial de carga das baterias, horário de chegada, horário de saída, frequência de carregamento, entre outras. Porém, considerar essa informação dentro do problema de planejamento de forma bem detalhada resulta altamente complexo. No entanto, existe a possibilidade de implementar um modelo de otimização bi-nível que permita simular a operação diária das ECVEs em um nível inferior, visando caracterizar a demanda associada aos VEs nas ECVEs para depois considerá-la dentro do problema de planejamento da expansão do SDEE em um nível superior.

2. Dado que este trabalho foi desenvolvido sob o suposto de que as ECVEs são propriedade dos OSDs, o modelo e o método proposto podem ser adaptados para considerar o caso em que as ECVEs são propriedade de terceiros. Nesse contexto, deveria existir um tipo de contrato entre as partes envolvidas resultando em um

benefício colectivo para os OSDs, os donos das ECVEs e os proprietários dos VEs (maximização do beneficio social). Esse modelo colaborativo estaria mais alinhado com os regulamentos atuais para a comercialização de energia requerida pelos VEs.

3. No contexto das redes inteligentes, os VEs, além de ser uma carga adicional, também podem atuar como fontes de armazenamento oferecendo diversas vantagens para os SDEEs através da tecnologia V2G. De acordo com os resultados das pesquisas correlatas, existe um novo conceito no contexto das redes de distribuição modernas, onde os VEs podem oferecer serviços auxiliares aos OSDs visando manter uma operação eficiente e confiável, por exemplo, uma das vantagens dos serviços auxiliares é o adiamento da expansão da rede. Assim, o modelo proposto neste trabalho poderia ser adaptado para considerar a possibilidade de que os VEs e/ou ECVEs forneçam potência à rede visando reduzir problemas técnicos na operação e adiar os investimentos associados à sua expansão.

4. Neste trabalho foram desenvolvidas restrições probabilísticas para a capacidade da subestação. Assim, a formulação proposta poderia ser estendida para considerar os limites operacionais (tensão e corrente) através de restrições probabilísticas. Alternativamente, poderiam se desenvolver modelos probabilísticos que permitam a incorporação das incertezas em todas as variáveis do sistema.

REFERÊNCIAS

ADAN, I.; RESING, J. **Queueing theory**. Eindhoven: Eindhoven University of Technology Press, 2002.

ALEM, D.; MORABITO, R. Planejamento da produção sob incerteza: programação estocástica versus otimização robusta. **Gestão & Produção**, São Carlos, v. 22, n. 3, p. 539–551, 2015.

AMINI, M. H.; ISLAM, A. Allocation of electric vehicles' parking lots in distribution network. In: 2014 IEEE PES INNOVATIVE SMART GRID TECHNOLOGIES CONFERENCE (ISGT) 2014, Washington, DC. **Proceedings** [...] Washington: IEEE, 2014. p. 1–5.

AUTOEVOLUTION. **Tesla motors**: models & brand history. Bucharest, 2019. Disponível em: https://www.autoevolution.com/tesla-motors/. Acesso em: 5 mar. 2019.

AUTOEVOLUTION. **Nissan leaf**: generations timeline, specs and pictures. Bucharest, 2019. Disponível em: https://www.autoevolution.com/nissan/leaf/. Acesso em: 5 mar. 2019.

BAGHERI, A.; MONSEF, H.; LESANI, H. Integrated distribution network expansion planning incorporating distributed generation considering uncertainties, reliability, and operational conditions. **International Journal of Electrical Power and Energy Systems**, Amsterdam, v. 73, p. 56–70, 2015.

BAÑOL ARIAS, M. N. **Aplicação de técnicas metaheurísticas para resolver o problema de coordenação de carregamento de veículos elétricos em sistemas de distribuição**. 2015. 142 f. Dissertação (Mestrado em Engenharia Elétrica) - Faculdade de Engenharia, Universidade Estadual Paulista, Ilha Solteira, 2015.

BANOL ARIAS, N. et al. Robust Joint Expansion Planning of Electrical Distribution Systems and EV Charging Stations. **IEEE Transactions on Sustainable Energy**, New York, v. 9, n. 2, p. 884–894, 2018.

BEALE, E. M. L. On Minimizing A Convex Function Subject to Linear Inequalities. **Journal of the Royal Statistical Society. Series B (Methodological)**, Kingdom, v. 17, n. 2, p. 173–184, 1955.

BEN-TAL, A.; EL GHAOUI, L.; NEMIROVSKI, A. **Robust optimization.** Princeton: Princeton University Press, 2009.

BERCKMANS, G. et al. Cost projection of state of the art lithium-ion batteries for electric vehicles up to 2030. **Energies**, Basel, v. 10, n. 9, 2017.

BERGGREEN, J. **Norwegian grid struggling to keep up with growing EV fleet**. Norway, 2017. Disponível em: https://evobsession.com/norwegian-grid-struggling-keep-growing-ev-fleet/. Acesso em: 16 out. 2018.

BERTOCCHI, M.; CONSIGLI, G.; DEMPSTER, M. A. H. **Stochastic optimization methods in finance and energy**. [S. l.]: Springer-Verlag New York, 2011.

BP. **BP energy outlook.** [S. l.], 2018. Disponível em: https://www.bp.com/content/dam/bp/en/corporate/pdf/energy-economics/energy-outlook/bp-energy-outlook-2018.pdf. Acesso em: 14 nov. 2018.

BRUNO, S. et al. Risk neutral and risk averse approaches to multistage renewable investment planning under uncertainty. **European Journal of Operational Research**, Amsterdam, v. 250, n. 3, p. 979–989, 2016.

BULKELEY, H.; PATERSON, M.; STRIPPLE, J. (ed.). **Towards a cultural politics of climate change: devices, desires and dissent**. Cambridge: Cambridge University Press, 2016.

CARLEY, S. et al. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. **Transportation Research Part D: Transport and Environment**, Amsterdam, v. 18, n. 1, p. 39–45, 2013.

CARRANO, E. G. et al. Electric distribution network expansion under load-evolution uncertainty using an immune system inspired algorithm. **IEEE Transactions on Power Systems**, New York, v. 22, n. 2, p. 851–861, 2007.

COMMITTEE ON CLIMATE CHANGE. **Reducing the UK's carbon footprint and managing competitiveness risks**. London: Committee on Climate Change, 2013. p. 1-110.

CHARNES, A.; COOPER, W. W. Deterministic Equivalents for Optimizing and Satisficing under Chance Constraints. **Operations Research**, Maryland, v. 11, n. 1, p. 18–39, 1963.

COELHO, J. M. **Impacto dos veículos elétricos no planejamento energético brasileiro:** setor de combustíveis fósseis. Rio de Janeiro: Empresa de Pesquisa Energética, 2017. p. 1-14.

COLE, J. 2014. **How much do public and home EV charging stations really cost?** [S. l.], 2016. Disponível em: http://insideevs.com/how-much-do-public-and-home-ev-charging-stations-really-cost/. Acesso em: 14 out. 2016.

COSSI, A. M. et al. Primary power distribution systems planning taking into account reliability, operation and expansion costs. **IET Generation, Transmission & Distribution**, Stevenage, v. 6, n. 3, p. 274, 2012.

CPLEX Optimization subroutine library guide and reference. Incline Village, NVCPLEX Division, 2008.

DANTZIG, G. B. Linear Programming under Uncertainty. **Management Science**, Maryland, v. 1, n. 3–4, p. 197–206, 1955.

DEHGHAN, S.; AMJADY, N.; CONEJO, A. J. Reliability-Constrained Robust Power System Expansion Planning. **IEEE Transactions on Power Systems**, New York, v. 31, n. 3, p. 2383–2392, 2016.

DUBEY, A.; SANTOSO, S. Electric vehicle charging on residential distribution systems: Impacts and mitigations. **IEEE Access**, New York, v. 3, p. 1871–1893, 2015.

EMPRESA DE PESQUISA ENERGÉTICA - EPE. **Demanda de energia 2050**. Rio de Janeiro, 2016.

FLETCHER, R. H.; STRUNZ, K. Optimal Distribution System Horizon Planning-Part I: Formulation. **IEEE Transactions on Power Systems**, New York, v. 22, n. 2, p. 791–799, 2007.

FOURER, R.; GAY, D. M.; KERNIGHAN, B. W. AMPL: **A modeling language for mathematical programming.** 2. ed. Pacific Grove: Brooks/Cole-Thomson Learning, 2003.

FRADE, I. et al. Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. **Transportation Research Record: Journal of the Transportation Research Board**, [S. l.], v. 2252, n. 12, p. 91–98, 2012.

FRANCO, J. F. et al. A mixed-integer LP model for the optimal allocation of voltage regulators and capacitors in radial distribution systems. **International Journal of Electrical Power and Energy Systems**, Amsterdam, v. 48, n. 1, p. 123–130, 2013.

FRANCO, J. F.; RIDER, M. J.; ROMERO, R. A mixed-integer quadratically-constrained programming model for the distribution system expansion planning. **International Journal of Electrical Power and Energy Systems**, Amsterdam, v. 62, p. 265–272, 2014.

FRANCO, J. F.; RIDER, M. J.; ROMERO, R. A mixed-integer linear programming model for the electric vehicle charging coordination problem in unbalanced electrical distribution systems. **IEEE Transactions on Smart Grid**, New York, v. 6, n. 5, 2200 – 2210, 2015.

FRANCO, J. F.; RIDER, M. J.; ROMERO, R. Robust Multi-Stage Substation Expansion Planning Considering Stochastic Demand. **IEEE Transactions on Power Systems**, New York, v. 31, n. 3, p. 2125–2134, 2016.

GANGULY, S.; SAHOO, N. C.; DAS, D. Multi-objective planning of electrical distribution systems using dynamic programming. **International Journal of Electrical Power and Energy Systems**, Amsterdam, v. 46, p. 65–78, 2013.

GEORGILAKIS, P. S.; HATZIARGYRIOU, N. D. A review of power distribution planning in the modern power systems era: Models, methods and future research. **Electric Power Systems Research**, Amsterdam, v. 121, p. 89–100, 2015.

GODINA, R. et al. Innovative impact assessment of electric vehicles charging loads on distribution transformers using real data. **Energy Conversion and Management**, Amsterdarm, v. 120, p. 206–216, 2016.

GONÇALVES, R. R. **Modelos de programação linear inteira mista para resolver problemas de otimização de sistemas de distribuição de energia elétrica radiais**. 2013. 221 f. Tese (Doutorado em Engenharia Elétrica) - Faculdade de Engenharia, Universidade Estadual Paulista, Ilha Solteira, 2013.

GONÇALVES, R. R. et al. Operation Planning of Electrical Distribution Systems Using a Mixed Integer Linear Model. **Journal of Control, Automation and Electrical Systems**, Campinas, v. 24, n. 5, p. 668–679, 2013.

GÖNEN, T.; RAMIREZ-ROSADO, I. J. Review of distribution system planning models: a model for optimal multistage planning. **IEE Proceedings C - Generation, Transmission and Distribution**, New York, v. 133, n. 7, p. 397–408, 1986.

HAFFNER, S. et al. Multistage model for distribution expansion planning with distributed generation - Part I: Problem formulation. **IEEE Transactions on Power Delivery**, New York, v. 23, n. 2, p. 915–923, 2008a.

HAFFNER, S. et al. Multistage Model for Distribution Expansion Planning with Distributed Generation - Part II: Numerical Results. **IEEE Transactions on Power Delivery**, New York, v. 23, n. 2, p. 924–929, 2008b.

HU, Z.; SONG, Y. Distribution network expansion planning with optimal siting and sizing of electric vehicle charging stations**.** In: INTERNATIONAL UNIVERSITIES POWER ENGINEERING CONFERENCE (UPEC), 47th, 2012. London. **Proceedings [...**] London: IEEE, 2012. v.1, p. 1-6.

HUMAYD, A. S. BIN; BHATTACHARYA, K. Distribution system planning to accommodate distributed energy resources and PEVs. **Electric Power Systems Research**, Amsterdam, v. 145, p. 1–11, 2017.

INTERNATIONAL ELECTROTECHNICAL COMMISSION (IEC) STANDARD. **61851-1:2010 Electric vehicle conductive charging system – Part 1: General requirements. 2010**, [S. l.], 2010.

INTERNATIONAL ENERGY AGENCY. **Global EV Outlook 2018**: towards cross-modal electrification. Paris, 2018. Disponível em: https://www.oecd-ilibrary.org/energy/global-ev-outlook-2018_9789264302365-en. Acesso em: 14 Nov. 2018.

INTERNATIONAL ENERGY AGENCY. **Global EV Outlook 2018**: towards cross-modal electrification. Paris: International Energy Agency, 2018. p. 1-141.

KOUTSOUKIS, N. C.; GEORGILAKIS, P. S.; HATZIARGYRIOU, N. D. A Tabu search method for distribution network planning considering distributed generation and uncertainties. In: INTERNATIONAL CONFERENCE ON PROBABILISTIC METHODS APPLIED TO POWER SYSTEMS, (PMAPS), 2014. Durham. **Proceedings** [...] Durham: IEEE, 2014. v.1, p. 1–6.

LACEY, G.; PUTRUS, G.; BENTLEY, E. Smart EV charging schedules: supporting the grid and protecting battery life. **IET Electrical Systems in Transportation**, Stevenage, v. 7, n. 1, p. 84–91, 2017.

LAVORATO, M. **Planejamento integrado da expansão de sistemas de distribuição de energia elétrica**. 2010. 216 f. Tese (Doutorado em Engenharia Elétrica) - Faculdade de Engenharia Elétrica e de Computação, Universidade Estadual de Campinas, Campinas, 2010.

LAVORATO, M. et al. A constructive heuristic algorithm for distribution system planning. **IEEE Transactions on Power Systems**, New York, v. 25, n. 3, p. 1734–1742, 2010.

LAVORATO, M. et al. Imposing radiality constraints in distribution system optimization problems. **IEEE Transactions on Power Systems**, New York, v. 27, n. 1, p. 172–180, 2012.

LINDNER, J. et al. 2018. **Governo cria meta de redução de 10% das emissões de combustíveis até 2028**. [S. l.], 2018. Disponível em: https://sustentabilidade.estadao.com.br/noticias/geral,governo-cria-meta-de-reducao-de-10-das-emissoes-de-combustiveis-ate-2028,70002339139. Acesso em: 14 Nov. 2018.

LIU, Z. et al. Optimal Planning of charging station for electric vehicle based on particle swarm optimization. In: IEEE PES INNOVATIVE SMART GRID TECHNOLOGIES, 2012. Tianjin. **Proceeding** [...] Tianjin: IEEE, 2012. v. 1, p. 1–5.

LIU, Z.; WEN, F.; LEDWICH, G. Optimal siting and sizing of distributed generators in distribution systems considering uncertainties. **IEEE Transactions on Power Delivery**, New York, v. 26, n. 4, p. 2541–2551, 2011.

LIU, Z.; WEN, F.; LEDWICH, G. Optimal planning of electric-vehicle charging stations in distribution systems. **IEEE Transactions on Power Delivery**, New York, v. 28, n. 1, p. 102–110, 2013.

LOPES, J. A. P.; SOARES, F. J.; ALMEIDA, P. M. R. Integration of Electric Vehicles in the Electric Power System. **Proceedings of the IEEE**, New York, v. 99, n. 1, p. 168–183, 2011.

LÓPEZ, J. C. et al. Robust optimisation applied to the reconfiguration of distribution systems with reliability constraints. **IET Generation, Transmission & Distribution**, Stevenage, v. 10, n. 4, p. 917–927, 2016.

LOTERO, R. C.; CONTRERAS, J. Distribution system planning with reliability. **IEEE Transactions on Power Delivery**, New York, v. 26, n. 4, p. 2552–2562, 2011.

MAHMOUDZADEH ANDWARI, A. et al. A review of Battery Electric Vehicle technology and readiness levels. **Renewable and Sustainable Energy Reviews**, Lausanne, v. 78, p. 414–430, 2017.

MARTINS, V. F.; BORGES, C. L. T. Active distribution network integrated planning incorporating distributed generation and load response uncertainties. **IEEE Transactions on Power Systems**, New York, v. 26, n. 4, p. 2164–2172, 2011.

MENDOZA, J. E. et al. Low voltage distribution planning considering micro distributed generation. **Electric Power Systems Research**, Amsterdam, v. 103, p. 233–240, 2013.

MENESES DE QUEVEDO, P.; MUNOZ-DELGADO, G.; CONTRERAS, J. Impact of Electric Vehicles on the Expansion Planning of Distribution Systems considering Renewable Energy, Storage and Charging Stations. **IEEE Transactions on Smart Grid**, New York, v. 10, n. 1, p. 794–804, 2019.

MIRANDA, V.; RANITO, J. V.; PROENCA, L. M. Genetic algorithms in optimal multistage distribution network planning. **IEEE Transactions on Power Systems**, New York, v. 9, n. 4, p. 1927–1933, 1994.

MIRZAEI, M. J.; KAZEMI, A.; HOMAEE, O. A Probabilistic Approach to Determine Optimal Capacity and Location of Electric Vehicles Parking Lots in Distribution Networks. **IEEE Transactions on Industrial Informatics**, New York, v. 12, n. 5, p. 1963–1972, 2016.

MONTOYA-BUENO, S.; MUNOZ, J. I.; CONTRERAS, J. A Stochastic Investment Model for Renewable Generation in Distribution Systems. **IEEE Transactions on Sustainable Energy**, New York, v. 6, n. 4, p. 1466–1474, 2015.

MORADIJOZ, M. et al. A multi-objective optimization problem for allocating parking lots in a distribution network. **International Journal of Electrical Power and Energy Systems**, Amsterdam, v. 46, n. 1, p. 115–122, 2013.

MUNOZ-DELGADO, G.; CONTRERAS, J.; ARROYO, J. M. Joint Expansion Planning of Distributed Generation and Distribution Networks. **IEEE Transactions on Power Systems**, New York, v. 30, n. 5, p. 2579–2590, 2015.

NEJADFARD-JAHROMI, S.; RASHIDINEJAD, M.; ABDOLLAHI, A. Multistage distribution network expansion planning under smart grids environment. **International Journal of Electrical Power and Energy Systems**, Amsterdam, v. 71, p. 222–230, 2015.

NEYESTANI, N. et al. Allocation of Plug-In Vehicles' Parking Lots in Distribution Systems Considering Network-Constrained Objectives. **IEEE Transactions on Power Systems**, New York, v. 30, n. 5, p. 2643–2656, 2015.

NICHOLAS, M.; HALL, D. **Lessons Learned on Early Electric Vehicle Fast-Charging Deployments**. Washington: International Council on Clean Transportation, 2018. p. 1-54.

NISSAN. **Nuevo nissan leaf**. [S. l.], 2019. Disponível em: https://www.nissan.es/vehiculos/nuevos-vehiculos/leaf/autonomia.html. Acesso em: 5 mar. 2019.

OLIVEIRA, F. **Otimização estocástica.** Minicurso. Ilha Solteira, 2013. Disponível em: http://www.feis.unesp.br/#!/departamentos/engenharia-eletrica/pesquisas-e-%0Aprojetos/lapsee/downloads/materiais-de-cursos/. Acesso em: 7 mar. 2017.

PARADA, V. et al. Heuristic determination of distribution trees. **IEEE Transactions on Power Delivery**, New York, v. 25, n. 2, p. 861–869, 2010.

PASHAJAVID, E.; GOLKAR, M. A. Optimal placement and sizing of plug in electric vehicles charging stations within distribution networks with high penetration of photovoltaic panels. **Journal of Renewable and Sustainable Energy**, New York, v. 5, n. 5, 2013.

PEREIRA JUNIOR, B. R. et al. Multiobjective multistage distribution system planning using tabu search. **IET Generation, Transmission & Distribution**, Stevenage, v. 8, n. 1, p. 35–45, 2014.

POPOVIĆ, Ž. N.; KERLETA, V. D.; POPOVIĆ, D. S. Hybrid simulated annealing and mixed integer linear programming algorithm for optimal planning of radial distribution networks with distributed generation. **Electric Power Systems Research**, Amsterdam, v. 108, p. 211–222, 2014.

POPOVIĆ, Ž. N.; POPOVIĆ, D. S. Graph theory based formulation of multi-period distribution expansion problems. **Electric Power Systems Research**, Amsterdam, v. 80, n. 10, p. 1256–1266, 2010.

PRÉKOPA, A. **Stochastic Programming**. [S. l.], Kluwer Academic Publishers, 1995.

QUEROL, X. **Strategies to encourage the use of electric, hybrid and gas vehicles in Central and Northern Europe**. [S. l: s. n.], 2016. Disponível em: http://airuse.eu/wp-content/uploads/2013/11/R18_AIRUSE-Encourage-clean-vehicles-CNE.pdf. Acesso em: 14 Nov. 2018.

QUIRÓS-TORTÓS, J. et al. Control of EV charging points for thermal and voltage management of LV networks. **IEEE Transactions on Power Systems**, New York, v. 31, n. 4, p. 3028–3039, 2016.

QUIRÓS-TORTÓS, J.; OCHOA, L. F.; LEES, B. **A statistical analysis of EV charging behavior in the UK**. In: IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM), 2015, Montevideo. **Proceeding** [...] Montevideo: IEEE, 2015. v. 1, p. 1-6.

RAMIREZ-ROSADO, I. J.; BERNAL-AGUSTIN, J. L. Genetic algorithms applied to the design of large power distribution systems. **IEEE Transactions on Power Systems**, New York, v. 13, n. 2, p. 696–703, 1998.

RAMIREZ-ROSADO, I. J.; DOMINGUEZ-NAVARRO, J. A. New Multiobjective Tabu Search Algorithm for Fuzzy Optimal Planning of Power Distribution Systems. **IEEE Transactions on Power Systems**, New York, v. 21, n. 1, p. 224–233, 2006.

SAMPER, M. E.; VARGAS, A. Investment Decisions in Distribution Networks Under Uncertainty With Distributed Generation—Part I: Model Formulation. **IEEE Transactions on Power Systems**, New York, v. 28, n. 3, p. 2331–2340, 2013.

SANDALOW, D. B. **Plug-In Electric Vehicles: What Role for Washington?** [S.l.], Brookings Institution Press, 2009.
SANKARAKRISHNAN, A.; BILLINTON, R. Sequential Monte Carlo simulation for composite power system reliability analysis with time varying loads. **IEEE Transactions on Power Systems**, New York, v. 10, n. 3, p. 1540–1545, 1995.

SCHUËLLER, G. I.; JENSEN, H. A. Computational methods in optimization considering uncertainties - An overview. **Computer Methods in Applied Mechanics and Engineering**, Amsterdam, v. 198, n. 1, p. 2–13, 2008.

SEDGHI, M.; ALIAKBAR-GOLKAR, M. Optimal storage scheduling in distribution network considering fuzzy model of PEVs. In: 18TH ELECTRIC POWER DISTRIBUTION NETWORK CONFERENCE, 2013, Kermanshah. **Proceeding** [...] Kermanshah: IEEE, 2013. v.1, p. 1-6.

SOCIETY OF AUTOMOTIVE ENGINEERS (SAE) STANDARD. **J1772:2010 Electric vehicle and plug in hybrid electric vehicle conductive charge coupler.** [S. l.], 2010.

SOUZA, B. B. et al. Immune system memetic algorithm for power distribution network design with load evolution uncertainty. **Electric Power Systems Research**, Amsterdam, v. 81, n. 2, p. 527–537, 2011.

TABARES, A. et al. Multistage Long-Term Expansion Planning of Electrical Distribution Systems Considering Multiple Alternatives. **IEEE Transactions on Power Systems**, New York, v. 31, n. 3, p. 1900–1914, 2016.

TAYLOR, J. et al. Evaluation of the impact of plug-in electric vehicle loading on distribution system operations. In: IEEE POWER AND ENERGY SOCIETY GENERAL MEETING, 2009, Calgary. **Proceeding** [...] Calgary: IEEE, 2009. v. 1, p. 1-6.

TESLA MOTORS. **Model charging**. USA: 2019. Disponível em: http://www.teslamotors.com/models-charging#/basics. Acesso em: 14 out. 2017.

UN-NOOR, F. et al. A comprehensive study of key electric vehicle (EV) components, technologies, challenges, impacts, and future direction of development. **Energies**, Basel, v. 10, n. 1217, p. 1–83, 2017.

VELDMAN, E.; VERZIJLBERGH, R. A. Distribution grid impacts of smart electric vehicle charging from different perspectives. **IEEE Transactions on Smart Grid**, New York, v. 6, n. 1, p. 333–342, 2015.

WANG, G. et al. Traffic-constrained multiobjective planning of electric-vehicle charging stations. **IEEE Transactions on Power Delivery**, New York, v. 28, n. 4, p. 2363–2372, 2013.

WANG, S. et al. Stochastic Collaborative Planning of Electric Vehicle Charging Stations and Power Distribution System. **IEEE Transactions on Industrial Informatics**, New York, v. 14, n. 1, p. 321–331, 2018.

XIONG, J. et al. Investigate the impacts of PEV charging facilities on integrated electric distribution system and electrified transportation system. **IEEE Transactions on Transportation Electrification**, New York, v. 1, n. 2, p. 178–187, ago. 2015.

YAO, W. et al. A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems. **IEEE Transactions on Power Systems**, New York, v. 29, n. 4, p. 1811–1821, 2014.

ZHANG, H. et al. An Integrated Planning Framework for Different Types of PEV Charging Facilities in Urban Area. **IEEE Transactions on Smart Grid**, New York, v. 7, n. 5, p. 2273–2284, 2016.

ZHANG, H. et al. A Second-Order Cone Programming Model for Planning PEV Fast-Charging Stations. **IEEE Transactions on Power Systems**, New York, v. 33, n. 3, p. 2763–2777, 2018.

ZHENG, Y. et al. Electric vehicle battery charging/swap stations in distribution systems: Comparison study and optimal planning. **IEEE Transactions on Power Systems**, New York, v. 29, n. 1, p. 221–229, 2014.

APÊNDICE A – DADOS DO SISTEMA DE 18 NÓS

Dados das linhas.					Dados da demanda (kVA).			
Linha [#]	de [i]	para [j]	l_{ij} [km]	$\theta_{ij,a}^{cir}$	Nó [#]	Estágio 1	2	3
1	1	5	2,220	0	1	4050	4735	5420
2	1	10	1,200	0	2	780	995	1210
3	1	15	2,200	1	3	2580	3380	3980
4	2	3	2,000	1	4	320	410	490
5	2	15	1,700	1	5	280	370	470
6	3	12	1,200	0	6	1170	1305	1440
7	3	17	1,200	0	7	4040	4200	4360
8	4	7	2,600	0	8	720	830	940
9	1	4	2,300	0	9	0	1150	1350
10	4	11	1,600	0	10	0	3050	3160
11	4	12	1,300	0	11	1620	1620	2200
12	5	6	2,400	1	12	0	0	1220
13	5	18	0,700	0	13	2160	2160	2400
14	6	9	1,200	0	14	0	0	2100
15	6	13	2,200	0	15	0	0	0
16	6	16	2,600	1	16	0	0	0
17	7	8	2,000	1	17	0	0	0
18	11	7	3,200	0	18	0	0	0
19	7	17	0,900	0				
20	8	16	2,000	1				
21	17	12	2,100	0				
22	10	14	1,000	0				
23	11	13	1,200	1				
24	13	16	1,500	1				
25	14	18	1,500	0				
26	18	9	2,100	0				

Fonte: Adaptado de (GÖNEN; RAMIREZ-ROSADO, 1986)

APÊNDICE B – DADOS DO SISTEMA DE 54 NÓS

Dados das linhas.					Dados da demanda (kVA).			
Linha	de	para	l_{ij}	$\theta_{ij,a}^{cir}$	Nó	Estágio		
[#]	[i]	[j]	[km]		[#]	1	2	3
1	51	1	1,405	1	1	3397,56	3912,34	4324,16
2	51	3	1,09	1	2	1132,52	1338,43	1544,34
3	3	4	1,56	1	3	411,825	514,782	720,694
4	4	7	1,25	1	4	1441,39	1956,17	1132,52
5	4	5	1,56	1	5	2059,13	2367,99	2676,86
6	7	8	1,56	1	6	617,738	720,694	720,694
7	5	6	1,25	1	7	205,913	514,782	1029,56
8	1	9	1,715	1	8	1544,34	1750,26	1956,17
9	1	2	1,56	1	9	1956,17	2059,13	1235,48
10	9	10	3,59	1	10	2059,13	2470,95	2985,73
11	52	14	1,875	1	11	205,913	308,869	308,869
12	14	15	1,875	1	12	1029,56	1647,3	1853,21
13	15	16	1,405	1	13	926,607	1029,56	1132,52
14	52	11	1,405	1	14	823,65	926,607	1029,56
15	11	12	1,56	1	15	1029,56	1235,48	1441,39
16	12	13	2,185	1	16	1338,43	1544,34	1956,17
17	19	20	1,56	0	17	514,782	617,738	720,694
18	18	19	1,25	0	18	926,607	1029,56	1235,48
19	17	18	2,03	0	19	1029,56	1235,48	1441,39
20	9	17	2,15	0	20	514,782	720,694	823,65
21	18	21	1,56	0	21	514,782	1647,3	1853,21
22	54	21	1,25	0	22	514,782	1029,56	1132,52
23	54	22	1,875	0	23	514,782	926,607	1029,56
24	9	22	2,34	0	24	514,782	411,825	514,782
25	22	23	1,715	0	25	617,738	823,65	926,607
26	23	24	1,405	0	26	0	823,65	1235,48
27	24	25	1,09	0	27	0	1235,48	1544,34
28	25	8	1,405	0	28	411,825	514,782	720,694
29	8	27	1,875	0	29	617,738	926,607	1441,39
30	27	26	1,715	0	30	2059,13	2367,99	2676,86
31	27	28	1,56	0	31	617,738	720,694	720,694
32	6	28	2,5	0	32	0	1544,34	1750,26
33	54	30	1,405	0	33	1853,21	2367,99	2985,73
34	30	29	1,56	0	34	926,607	1029,56	1235,48
35	30	43	2,03	0	35	0	0	926,607
36	43	37	1,25	0	36	205,913	205,913	308,869
37	37	31	0,935	0	37	1029,56	1647,3	2162,08
38	31	10	1,56	0	38	0	0	1132,52
39	13	43	1,875	0	39	823,65	926,607	1029,56
40	12	45	1,25	0	40	1029,56	1235,48	1441,39

Fonte: Adaptado de (GÖNEN; RAMIREZ-ROSADO, 1986)

Dados das linhas.					Dados da demanda (kVA).			
Linha	de	para	l_{ij}	$\theta_{ij,a}^{cir}$	Nó	Estágio		
[#]	[i]	[j]	[km]		[#]	1	2	3
41	45	44	1.09	0	41	308.869	514.782	926.607
42	44	38	1.56	0	42	0	0	1235.48
43	38	39	1.715	0	43	0	0	1338.43
44	39	32	2.03	0	44	514.782	1029.56	1441.39
45	39	33	1.405	0	45	514.782	514.782	823.65
46	33	8	2.34	0	46	0	1647.3	1853.21
47	33	34	0.935	0	47	514.782	514.782	1029.56
48	34	35	1.09	0	48	514.782	617.738	823.65
49	35	36	1.09	0	49	0	617.738	514.782
50	53	36	1.25	0	50	0	0	823.65
51	53	28	1.56	0	51	0	0	0
52	53	41	1.56	0	52	0	0	0
53	41	40	1.25	0	53	0	0	0
54	40	16	1.25	0	54	0	0	0
55	41	42	1.875	0				
56	42	48	1.25	0				
57	48	49	1.875	0				
58	49	50	1.09	0				
59	42	47	1.56	0				
60	47	46	1.56	0				
61	46	14	1.715	0				

Fonte: Adaptado de (GÖNEN; RAMIREZ-ROSADO, 1986)

APÊNDICE C – LINEARIZAÇÃO POR PARTES

A linearização por partes é usada para definir a função *f*, a qual calcula o valor quadrado da variável ρ, limitada pelo intervalo $[0, \bar{\rho}]$. Se o intervalo é particionado em Γ blocos do mesmo tamanho, o conjunto de partição $\mathcal{P} = \{0, \bar{\rho}/\Gamma, 2\bar{\rho}/\Gamma, \ldots, \bar{\rho}\}$ seria definido de modo que cada bloco teria um comprimento igual à $\bar{\rho}/\Gamma$. Considerando que $\Delta_{\rho,\gamma}$ é uma variável continua que define o valor do n-th bloco na partição $\mathcal{P}$, a aproximação linear por partes de ρ^2 é dada por (89)−(93). Este tipo de função apresenta a seguinte estrutura geral:

$$f(\rho, \bar{\rho}, \Gamma) = \sum_{\gamma=1}^{\Gamma} m_{\rho,\gamma} \Delta_{\rho,\gamma} \tag{89}$$

$$\rho^{+} - \rho^{-} = \rho \tag{90}$$

$$\rho^{+} + \rho^{-} = \sum_{\gamma=1}^{\Gamma} \Delta_{\rho,\gamma} \tag{91}$$

$$0 \le \Delta_{\rho,\gamma} \le \bar{\rho}/\Gamma \qquad \forall \gamma = 1,..,\Gamma \tag{92}$$

$$m_{\rho,\gamma} = (2\gamma - 1)\bar{\rho}/\Gamma \qquad \forall \gamma = 1,..,\Gamma \tag{93}$$

Em que Γ é o número de discretizações usadas na função *f*; $m_{\rho,\gamma}$ é o declive do γth bloco da discretização por partes de ρ; $\Delta_{\rho,\gamma}$ é o valor da γth variável auxiliar usada na dicretização de ρ; e ρ^{+} e ρ^{-} são variáveis auxiliares positivas usadas no cálculo de $|\rho|$.

APÊNDICE D – TRABALHOS RELEVANTES

Neste apêndice são apresentados os trabalhos relevantes publicados em revistas internacionais e que foram desenvolvidos durante o andamento do doutorado.

1. M. N. Bañol; A. Tabares; J. F. Franco; M. Lavorato; R. Romero. **Robust Joint Expansion Planning of Electrical Distribution Systems and EV Charging Stations**. *IEEE Transactions on Sustainable Energy*, vol. 9, no. 2, pp. 884-894, April 2018.

2. M. N. Bañol; M. Lavorato; J.F. Franco; R. Romero. **Metaheuristic optimization algorithm for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation**. *Electric Power Systems Research*, vol. 142, pp. 351-361, January 2017.

APÊNDICE E – TRABALHOS CORRELATOS

Neste apêndice são apresentadas as pesquisas correlatas que foram desenvolvidas durante o trabalho de doutorado sanduíche no exterior. Os tópicos apresentados são:

a) **Resultados da operação real de uma frota de VEs que fornece serviços de regulação de frequência ao operador do sistema de transmissão na Dinamarca através da tecnologia V2G, no âmbito do projeto de integração de VEs nos sistemas de potência "Parker-project".** Foi feita uma análise dos problemas práticos que podem aparecer na hora de realizar implementações realistas de regulação de frequência, tais como atrasos, erros de medição e restrições físicas dos equipamentos. A identificação desses problemas práticos torna-se útil na hora de desenvolver estratégias de controle da carga e descarga dos VEs para fornecer qualquer tipo de serviço para os operadores do sistema de transmissão ou distribuição. Os resultados demonstram que um conjunto de VEs operando de forma agregada é capaz de ajudar a melhorar a operação da rede enquanto são também atendidos os requerimentos de energia dos VEs para cobrir o objetivo principal da frota de VEs, o qual é o transporte de usuários.

b) **Uma revisão da literatura e classificação dos serviços potenciais que os VEs podem proporcionar especialmente aos operadores do sistema de distribuição no contexto das redes inteligentes.** Com o advento das redes inteligentes, novos dispositivos como VEs, baterias, e fontes renováveis estão sendo integrados nas redes de distribuição trazendo grandes desafios no planejamento da operação dos SDEEs. Assim, os SDEEs precisam assumir novas responsabilidades e procurar serviços auxiliares para manter e oferecer um serviço de alta qualidade aos consumidores finais. Porém, o conceito de serviços auxiliares fornecidos para os SDEEs é um novo paradigma. Por tanto, não existe ainda um mercado definido para esses serviços nem regulações para interação entre as partes envolvidas, ou seja, OSDs, usuários proprietários de VEs e/ou outras entidades que atuem como mediadoras entre eles como são por exemplo os agregadores. Além disso, os OSDs ainda não estão habilitados para procurar serviços que permitam manter a operação eficiente e confiável da rede. De fato, as atividades dos OSDs concentram-se principalmente no planejamento e desenho de longo prazo, mais do que na operação em tempo real. Porém, em redes modernas de distribuição, a qualidade do serviço pode ser mantida através de serviços fornecidos por esses novos recursos de energia, aproveitando a sua flexibilidade e permitindo-lhes realizar atividades no curto prazo. Nesse contexto, a maioria das estratégias desenvolvidas para ajudar à operação do SDEE através dos VEs permanecem em conceitos teóricos, que trabalham baseados em vários supostos que impediriam sua implementação em aplicações reais.

Assim, neste trabalho é apresentada uma descrição detalhada dos serviços mais recentes e das abordagens utilizadas na literatura para fornecer serviços aos OSDs através dos VEs. Adicionalmente é proposta uma avaliação da maturidade desses serviços em termos de quão longe estão as metodologias até agora apresentadas na literatura para serem implementadas em aplicações da vida real e quão fácil esses serviços poderiam ser combinados com o serviço de regulação de frequência, dado que já existem aplicações reais de regulação de frequência em alguns países do mundo, como os Estados Unidos e a Dinamarca. Finalmente são discutidos os principais aspectos que precisam ser abordados para implementar serviços fornecidos pelos VEs para os OSDs em aplicações da vida real. Os resultados mostram que os aspectos mais importantes que devem ser aprofundados para alcançar esse alvo estão relacionados com a estrutura de mercado, a definição do sistema de lucro ao nível do sistema de distribuição e benefícios econômicos, degradação da bateria, e impactos sob a rede de distribuição pela prestação de serviços aos OSTs.

c) **Uma avaliação do benefício econômico que os usuários proprietários de VEs podem obter quando participam em mercados de regulação de frequência primária.** VEs habilitados com a tecnologia V2G podem ajudar os sistemas de potência fornecendo diversos serviços auxiliares, e.g., regulação de frequência, regulação de tensão, redução de congestionamentos, entre outros. Regulação de frequência é um dos serviços mais procurados pelos OSTs para manter o balanço entre a geração e o consumo em um horizonte de planejamento de curto-prazo (diário ou horário). Os VEs são uma boa opção para fornecer este tipo de serviços já que eles permanecem imóveis uma grande parte do tempo proporcionando certo grau de flexibilidade para o controle da sua carga ou descarga. Além disso, os VEs são comprados com um propósito principal o qual é o transporte de passageiros. Assim, a provisão de serviços poderia gerar lucros alternativos para os proprietários quando o veículo não está sendo usado para seu fim principal. O benefício económico pela provisão de regulação de frequência depende de diferentes aspectos, tais como a estrutura de pagamento, a estrutura do mercado, as estratégias de operação, os custos de degradação da bateria, penalizações por incumprimento do serviço, ou por causar problemas técnicos nas redes de distribuição. Assim, neste trabalho é apresentada uma metodologia para o cálculo do benefício econômico que os usuários de VEs poderiam obter pela provisão de serviços de regulação de frequência primária. A metodologia define a oferta de potência que maximiza o lucro considerando a influência de três estratégias de operação e as preferências dos usuários (e.g., por exemplo, necessidades de mobilidade de cada motorista e autonomia mínima). O benefício econômico é avaliado incluindo os custos associados à indisponibilidade do serviço, à degradação da bateria e ao impacto negativo causado na rede de distribuição. Os resultados estimam benefícios anuais que variam entre €200 e €2000 por veículo, o que demonstra que os proprietários de EV podem obter lucros substanciais por participar em mercados de regulação de frequência primária.

A seguir serão apresentados em detalhe cada um dos trabalhos acima mencionados através dos artigos publicados e/ou preparados para publicação.

Robust Joint Expansion Planning of Electrical Distribution Systems and EV Charging Stations

Nataly Bañol Arias, Alejandra Tabares, John F. Franco, *Member, IEEE,* Marina Lavorato, *Member, IEEE,* and Rubén Romero, *Senior Member, IEEE*

***Abstract*—Electrical Distribution Systems (EDSs) should be prepared to cope with demand growth in order to provide a quality service. The future increase in Electric Vehicles (EVs) represents a challenge for the planning of the EDS, due to the corresponding increase in the load. Therefore, methods to support the planning of the EDS, considering the uncertainties of conventional loads and EV demand, should be developed. This paper proposes a mixed-integer linear programming (MILP) model to solve the robust multistage joint expansion planning of EDSs and the allocation of EV charging stations (EVCSs). Chance constraints are used in the proposed robust formulation to deal with load uncertainties, guaranteeing the fulfillment of the substation capacity within a specified confidence level. The expansion planning method considers the construction/reinforcement of substations, EVCSs, and circuits, as well as the allocation of distributed generation units and capacitor banks along the different stages in which the planning horizon is divided. The proposed MILP model guarantees optimality by applying classical optimization techniques. The effectiveness and robustness of the proposed method is verified via a 18-node test system. Additionally, Monte Carlo simulations are carried out, aiming to verify the compliance of the proposed chance constraint.**

***Index Terms*—Chance constraint, electrical distribution systems, electric vehicle charging stations, mixed-integer linear programming, multistage expansion planning.**

I. Introduction

THE use of Electric Vehicles (EVs) is expected to increase in the next few years as an option for resolving environment problems, such as climate change [1]. The adoption of EVs contributes to the reduction of air pollutant emissions and could take advantage of renewable energy sources when the EV batteries need to be charged. However, the electrical distribution system (EDS) should be prepared to contend with an increase in demand related to EV charging.

Household charging is the first choice for EV owners, although the corresponding slow charging mode is time-consuming [2]. On the other hand, electric vehicle charging stations (EVCSs) are a suitable option for EV charging, as they could avoid overloading residential distribution networks, while allowing both slow (preserving battery lifespan) and fast charging modes. EVCSs could also offer lower energy prices and reduce charging time (similar to the refueling of conventional vehicles) when compared to residential charging. These benefits will potentially encourage the use of EVs.

A high penetration of EVs in residential and commercial areas could result in operational problems, such as overloads, voltage issues, and excessive energy losses [3]. Therefore, the EDS expansion planning should satisfy the energy requirements of upcoming EV penetration for both household charging and EVCSs.

The solution of the EDS expansion planning problem identifies the investments needed to supply the future loads while satisfying operational constraints. This optimization problem is highly complex and *NP-hard*, due to the binary variables that represent the construction and/or allocation of new equipment and the high number of continuous variables used to represent the steady-state operation of the network. This problem has been widely studied, using different mathematical models and solution techniques. Nonetheless, the expansion planning of the EDS, considering the high penetration of EVs, needs to be studied further. A complete literature review of the EDS expansion planning problem can be found in [4].

Methods based on evolution algorithms and Mixed-Integer Linear Programming (MILP) have been developed to solve the EDS expansion planning problem considering the integration of EVs [5]–[8]. The allocation of EV battery charging/swap stations is carried out in [5] to minimize the costs related to reinforcement and adaption (construction costs necessary to cover the insufficiency of the plan). A method to solve the multistage EDS expansion planning problem, which takes into account the allocation and sizing of EVCSs, is proposed in [6]. Similarly, in [7] and [8], the joint expansion planning of EDS and EVCSs is addressed. In [7], the authors establish a bi-objective deterministic collective planning model for EDS that considers EVCSs, although the stochastic behavior of EV users, along with different EV charging modes, is disregarded. Moreover, the increase in the annual demand, impacts of the geographic locations, and time periods of fast- and slow-charging modes, in the expansion planning are not considered. In order to overcome those limitations, the authors in [8] propose a stochastic multistage collaborative planning model for EDS that considers EVCSs, slow- and fast-charging modes, and battery exchange. Nevertheless, the metaheuristic technique used to solve the problem does not provide information related to the quality of the solution (e.g., the distance from the obtained solution to the optimal solution), and there is not a way to define the level of confidence to address uncertainties related to demand profiles. On the other hand, the allocation

This work was supported by the Brazilian institutions CAPES, FAPESP and CNPq process No. 152002/2016-2.

N. Bañol Arias, A. Tabares, J. F. Franco, and R. Romero are with the Faculdade de Engenharia de Ilha Solteira – Universidade Estadual Paulista (UNESP), Departamento de Engenharia Elétrica, Ilha Solteira, São Paulo, Brazil. E-mails: {natycanta, tabares.1989, jffranco}@gmail.com; ruben@dee.feis.unesp.br.

M. Lavorato is with CEATEC – Pontifícia Universidade Católica de Campinas (PUC-CAMPINAS), Campinas, São Paulo, Brazil. E-mail: marina.oliveira@pu-campinas.edu.br.

of Distributed Generation (DG) units and Capacitor Banks (CB), is also disregarded in [5]–[8]. The installation of these equipment's should also be included in the expansion planning, as they could defer reinforcement, resulting in the reduction of investments [9].

The allocation and sizing problem of EVCSs is studied in [10]–[17]; nevertheless, these approaches solve the problem without considering the joint expansion planning of the whole grid. Reference [10] models the EVCS behavior, taking into account market interactions (reserve and energy markets), DG units operation and enforce network constraints in a two-stage approach. However, the proposed methodology in [10] is mostly focused on the EVCS operation planning. Similarly, in [11], a two-stage methodology to solve the optimal planning of EVCSs was proposed. Environmental factors, service radius, and different charger types are included in the proposed method; however, the authors disregarded the operation of both CBs and DG units, and the inclusion of different types of EVs. Metaheuristic techniques, such as genetic algorithms [12]–[14] and particle swarm optimization [16], [17], have also been used to solve the optimal allocation and sizing of EVCSs. From those works, only [17] considers the operation of DG units within the method. Moreover, in contrast to classical optimization techniques (such as those used in this paper), the main disadvantage of the metaheuristic techniques is that they do not guarantee optimal solutions.

Different from the previous works, authors in [18] present a new methodology for the optimal allocation of EVCSs based on a sustainability perspective. A multicriteria decision-making (MCDM) method, along with a fuzzy TOPSIS method, are used to take into account aspects related to economic growth, social development, and environmental protection. The EVCS allocation decision is carried out based on the criteria of five groups of expert panels, without considering mathematical models to represent the problem. This methodology allows for the consideration of quantitative and qualitative criteria, which are important in the allocation and sizing of EVCSs. However, from the EDS point of view, technical aspects of the grid operation should be verified.

Uncertainties associated with the growth of conventional loads and EV demand should be considered in the EDS expansion planning problem in order to reduce risks and avoid underinvestment, which could lead to operational problems. From the aforementioned references, [5], [10], [13], and [17] consider both the uncertain behavior of EVs as well as the operational constraints of the EDS, whereas [14] only considers the uncertain behavior of EVs. In [5], the uncertainty associated with EV demand is addressed using a geometric Brownian motion approach, while in [10], it is dealt with a two-stage stochastic programming model, along with an approach for generation of scenarios. Moreover, in [13] and [14], the authors represent the uncertainties of the EVs through probabilistic parameters and probability distribution functions for the arrival and SOC data, while in [17], the hourly aggregated load demand of EVs is estimated using a non-Gaussian multivariate stochastic model provided by copula functions. Nevertheless, none of those studies considers the uncertainty associated with the conventional loads.

Most of the aforementioned methods focus on modeling the allocation and sizing of the EVCSs based on their planning operation. In contrast to them, the main purpose of the proposed method is to consider the allocation and sizing of the EVCSs within the expansion planning of the EDS, in order to illustrate the impact of the EV integration in distribution systems, according to the EV connection point.

This paper presents a MILP model used to solve the robust multistage joint expansion planning of EDSs and the allocation of EVCSs. The proposed robust formulation uses chance constraints to deal with the uncertainties related to conventional loads and EV demand, guaranteeing the fulfillment of the substation capacity within a specified confidence level. The expansion planning method considers the construction/reinforcement of substations, EVCSs, and circuits, as well as the allocation of DG units and CBs along the different stages in which the planning horizon is divided. Similarly to [9], piecewise linearization was used to represent the square of active and reactive powers in the equations that model the steady-state operation of the EDS. Therefore, the proposed method is a MILP formulation that can be solved guaranteeing optimality using commercial solvers such as CPLEX. The main contributions of this paper relies on the application of

1) A chance constraint stochastic programming framework [19], which is suitable for addressing the uncertainties related to conventional loads and EV demand in the EDS expansion planning. This approach ensures the fulfillment of the substation capacity (the most important equipment of the network) within a confidence level, as was done in [20];
2) Linearizations and simplifications, formulated in order to consider the stochastic behavior of conventional loads and EV demand in the EDS expansion planning problem. In contrast to other works, which use methods based on chance constraint stochastic programming, the proposed formulation makes it possible to incorporate different network equipment, such as DG units and CBs;
3) A mixed-integer linear formulation for the EDS expansion planning, which guarantees finite convergence to optimality while providing a measure of the distance to the optimum solution [21], and for which efficient software is available [22];
4) A novel analysis of the EV integration in distribution systems, which examines the impact of EV demand on the multistage expansion planning of EDS according to the connection point, along with a comparative analysis, which shows the benefits of including the uncertainty of the conventional loads and EV demand in the distribution planning when compared with deterministic models.

The effectiveness and robustness of the proposed method is verified via a 18-node and 54-node test system. Additionally, Monte Carlo simulations are carried out, aiming to verify the compliance of the proposed chance constraint.

II. Multistage Expansion Planning of EDSs, Considering EVCSs

As discussed in the previous section, the main goal of the EDS expansion planning is to adequately meet the load growth with a minimum total cost, subject to a set of technical and operational constraints. The complexity of the distribution planning has been increased over the past few years, due to the emergence of new network elements and the stochastic behavior of new loads (e.g., plug-in electric vehicles). In this context, the proposed method defines the investments needed to satisfy the load growth while keeping a suitable operation. The construction/reinforcement of substations and circuits is analyzed along different stages of the planning horizon, in an attempt to minimize the total investment and operational cost. In addition, DG units and CBs are considered, in order to improve the operation.

The expansion planning of the EDS should also take into account the allocation and sizing of EVCSs (from a set of suitable candidate nodes), which provide the energy required to charge EVs. Since previous works have focused on the operation of EVCSs without considering the expansion of the network [10]–[17], the proposed model is aimed toward a joint expansion planning of EDS and EVCSs. For this purpose, the operation of an EVCS and the corresponding EV charging process should be represented. However, the formulation of this charging process within the expansion planning is complex. Due to this fact, some details related to the operation of an EVCS are simplified within the formulation of the expansion planning. For instance, the EVCS operation issues (i.e., difference in the EV arrivals, waiting/idle times, and charging coordination) are simplified, assuming that the corresponding power is demanded in a typical day during a specific period of time (e.g., 12 hours), represented by dw^{cs}.

It is assumed that not all the EVs arrive at the EVCS at the same time; it is further assumed that the charging operation follows a "first come, first served" sequence. Thus, if an EV arrives while all of the chargers are in use, it has to wait until the next charger becomes available. The fact that the EVs have different states of charge (SOC) at arrival is represented by the factor ϕ_{soc}, which depends on each EV type, the daily distance driven, and other aspects related to the behavior of the EV owners. This factor is considered as the mean value of the SOC, which usually is represented by a Gaussian distribution function.

The proposed formulation identifies the optimal solution for the EVCSs, i.e., their location and the minimum number of chargers of each type required to meet the EV demand in each stage along the planning horizon. In order to represent the worst case for the EDS operation, it is assumed that the chargers are connected simultaneously and are demanding their rated power from the grid.

The following assumptions are made in order to formulate a mathematical model for the multistage EDS expansion planning problem considering EVCSs:

1) Given an EV penetration for each stage, the allocation and sizing of EVCSs is proposed by the distribution system operator, as considered in [5], [6], [10], [11]. This idea stems from the fact that the EDS must be prepared to satisfy the charging requirements resulting from the expected increase of the EV demand;
2) A fraction of the EVs are charged in the EVCSs, while the rest are charged at home, therefore, increasing the conventional load;
3) The EVs can be recharged using two charger types (fast or slow chargers).

Uncertainties related to the growth of conventional loads and EV demand are handled in the proposed model through chance constraints (see Section III-G), which guarantee the fulfillment of the substation capacity within a specified confidence level. It is assumed that the power related to the conventional loads and the number of EVs connected in the EDS are independent normal variables, as discussed in [23], i.e., there is not a correlation between the variables, which facilitates the calculation of the mean value and the standard deviation of the substation's apparent power.

III. Mathematical Model

The multistage EDS expansion planning problem can be mathematically formulated as a mixed-integer nonlinear programming (MINLP) model, which is highly complex to solve [24], [25]. Thus, linearization techniques can be used in order to transform the formulation into an MILP model. The proposed MILP formulation, which is based on [9], is used for solving the robust multistage joint expansion planning of EDSs and the allocation of EVCSs.

Due to the complexity of the EDS expansion planning and the relatively high substation investment cost, the proposed robust formulation uses chance constraints, which consider uncertainties related to conventional loads and EV demand, to enforce the capacities of the substations. The uncertainty of the conventional load and EV demand is modeled through a known normal distribution variable for the loads, as well as for the number of EVs that should be charged in each stage of the planning horizon. On the other hand, voltage and current limits are imposed in a deterministic way, i.e., mean values are assumed for the demands.

Equations that represent the influence of EVCSs on the EDS expansion planning, are presented in this section. Due to the lack of space, equations related to the operational limits of CBs and DG units, as well as the radiality conditions, are not shown. However, a complete definition of these constraints can be found in [9].

The following index will be used to represent the corresponding sets: a, b, c for conductor types; i for nodes; h, t, r for substation alternatives; e for charger types; g for DG unit alternatives; s for substation nodes; ij, kj for circuits; u, k for stages; v for EV types; p for EVCS nodes; and m for DG unit nodes.

A. Objective Function

The objective function minimizes the total expansion planning cost, comprising the investment, the operational, and the energy loss costs along the planning horizon. The investment costs in the circuits (IC), substations (IS), capacitors banks (ICB), and DG units (IDG) are calculated by (1)-(4), respectively. This set of equations is written in terms of the variables that represent the investment decisions. Thus, the binary investment variable $x^{cir}_{ij,a,b,u}$ that represents the construction/reinforcement (using conductor type b and assuming initial type a) is used to calculate the investment in the circuit, considering the conductor type cost ($c^c_{ij,a,b}$) and its length (l_{ij}). In a similar way, the cost related to the substations is calculated by using the binary variable for construction/reinforcement $x^{sub}_{s,h,t,u}$ (using substation type t and assuming initial type h) and the corresponding cost $c^s_{s,h,t}$. Moreover, the cost of CBs depends on the decision variables (binary for installation, $x^{cb}_{i,u}$, and integer for the number of standard capacitor units, $n^{cbi}_{i,u}$) and the corresponding costs (c^{cb} for installation and c^{mod} per module). The investment in DG units is calculated according to the binary installation variable $x^{dg}_{m,g,u}$ and the installation cost c^{dg}_g.

The cost associated with the EVCS (ICS) is calculated by (5) in terms of the decision variables (binary for the allocation and integer for the number of chargers, $x^{cs}_{p,u}$ and $n^{chi}_{p,e,u}$, respectively) and the installation costs (parameters c^{cs} and c^c_e for the EVCS and the chargers, respectively). Note that the maintenance cost and operational cost of the EVCS are not considered explicitly, although they can be included within the installation costs.

$$IC = \sum_{ij}\sum_{a}\sum_{b} c^c_{ij,a,b} x^{cir}_{ij,a,b,u} l_{ij} \tag{1}$$

$$IS = \sum_{s}\sum_{h}\sum_{t} c^s_{s,h,t} x^{sub}_{s,h,t,u} \tag{2}$$

$$ICB = \sum_{i} \left(c^{cb} x^{cb}_{i,u} + c^{mod} n^{cbi}_{i,u}\right) \tag{3}$$

$$IDG = \sum_{m}\sum_{g} c^{dg}_g x^{dg}_{m,g,u} \tag{4}$$

$$ICS = \sum_{p}\sum_{e} \left(c^{cs} x^{cs}_{p,u} + c^c_e n^{chi}_{p,e,u}\right) \tag{5}$$

The energy cost (EC) and the operational cost of substations (OS) are calculated by (6) and (7). The EC is written in terms of the cost of the energy imported by the substation (c^e), the energy cost of the DG units (c^{edg}_g), and the corresponding active powers $P^S_{s,u}$ and $P^{GD}_{m,u}$, multiplied by the number of hours in one year (α) and the load factor (ϕ_l). The OS is calculated using the apparent power supplied by the substation that depends on the square approximation of the active and reactive power ($P^S_{i,u}$ and $Q^S_{i,u}$, respectively), the operation cost (c^v_s), and the loss factor ϕ_s. Moreover, the function $f(\rho, \overline{\rho}, \Gamma)$ represents a piecewise linearization of the square value of a variable ρ, and it is written in terms of its maximum value $\overline{\rho}$ and the number of discretization intervals Γ, as described in the appendix.

The function $\zeta(\tau, K) = (1-(1+\tau)^{-K})\tau^{-1}$ in (6) and (7) is used to calculate the present value of an annualized cost that has a duration of K years in terms of the interest rate τ. Thus, K represents the number of years of each stage.

$$EC = \alpha\phi_l \left(\sum_{s} c^e P^S_{s,u} + \sum_{m}\sum_{g} c^{edg}_g P^{DG}_{m,u}\right) \zeta(\tau, K) \tag{6}$$

$$OS = \sum_{s} \alpha\phi_s c^v_s \sum_{t} \left[f(P^S_{s,u}, \overline{S}_t, \Gamma) + f(Q^S_{s,u}, \overline{S}_t, \Gamma)\right] \zeta(\tau, K) \tag{7}$$

Therefore, the objective function is defined as

$$\min \sum_{u} \frac{IC + IS + ICB + IDG + ICS + EC + OS}{(1+\tau)^{-(u-1)K}} \tag{8}$$

B. Fundamental Constraints of the EDS

The set of equations (9)-(12) corresponds to Kirchhoff's laws and represents the operation of radial EDSs [9]. Constraints (9) and (10) represent the active and reactive power balance, which guarantee that all loads are supplied, i.e., Kirchhoff's first law. Constraint (11) calculates the current magnitude throughout the circuit ij, while constraint (12) defines the voltage drop in the circuit ij in terms of its connection status (represented by the binary variable $y^{cir}_{ij,a,u}$), the active and reactive power flows ($P_{ij,a,u}$ and $Q_{ij,a,u}$), and the square of the current ($I^{sqr}_{ij,a,u}$). These variables are different from zero only if the corresponding conductor type a is chosen, i.e., $y^{cir}_{ij,a,u}$ is equal to one. Thus, (11) and (12) represent Kirchhoff's second law for each fundamental loop.

$$\sum_{kj}\sum_{a} P_{kj,a,u} - \sum_{ij}\sum_{a}(P_{ij,a,u} + R_a l_{ij} I^{sqr}_{ij,a,u}) + P^S_{i,u} + \sum_{g} P^{DG}_{i,g,u} = P^D_{i,u} + \sum_{e} n^{cho}_{i,e,u} P^{ch}_e \quad \forall i, u \tag{9}$$

$$\sum_{kj}\sum_{a} Q_{kj,a,u} - \sum_{ij}\sum_{a}(Q_{ij,a,u} + X_a l_{ij} I^{sqr}_{ij,a,u}) + n^{bco}_{i,u} Q^{cb} + Q^S_{i,u} + \sum_{g} Q^{DG}_{i,g,u} = Q^D_{i,u} \quad \forall i, u \tag{10}$$

$$V'^2_{j,u} I^{sqr}_{ij,a,u} = f\left(P_{ij,a,u}, \overline{V}\,\overline{I}_a, \Gamma\right) + f\left(Q_{ij,a,u}, \overline{V}\,\overline{I}_a, \Gamma\right) \quad \forall ij, a, u \tag{11}$$

$$\left|V^{sqr}_{i,u} - V^{sqr}_{j,u} - \sum_{a}[2(R_a P_{ij,a,u} + X_a Q_{ij,a,u}) l_{ij} + Z^2_a l^2_{ij}\, I^{sqr}_{ij,a,u}]\right| \le \left(\overline{V}^2 - \underline{V}^2\right) \sum_{a}(1 - y^{cir}_{ij,a,u}) \quad \forall ij, u \tag{12}$$

The EV demand is represented on the right-hand side of (9) as the product of the rated active power of each charger type (P^{ch}_e) and the number of chargers operating in the corresponding EVCS ($n^{cho}_{i,e,u}$). The set of equations above uses the following variables and parameters: $P^D_{i,u}$ and $Q^D_{i,u}$ are the active and reactive power demands at node i; R_a, X_a, and Z_a are the resistance, reactance, and impedance per length of conductor type a, respectively; $n^{cbo}_{i,u}$ is the number of standard capacitor units operating at node i, while Q^{cb} is the reactive power of each capacitor unit; $Q^{DG}_{i,g,u}$ is the reactive power supplied by the DG unit at node i. $\underline{V}$ and $\overline{V}$ are the lower and upper voltage limits, respectively, while $\overline{I}_a$ is the current limit of conductor type a. The parameter $V'_{j,u}$ is the estimated voltage at node i, and it is used to obtain a linear expression on the left-hand side of (11), as proposed in [9].

Operational constraints, such as voltage and current limits in the system, are defined by (13) and (14), respectively.

$$\underline{V}^2 \le V_{i,u}^{sqr} \le \overline{V}^2 \quad \forall i,u \tag{13}$$

$$0 \le I_{ij,a,u}^{sqr} \le \overline{I}_a^{\,2} y_{ij,a,u}^{cir} \quad \forall ij,a,u \tag{14}$$

C. Logical Constraints Associated with Substations

Constraints (15)-(19) allow for the coordination of the investment and operation of the substations along the planning horizon. The investment types correspond to the available apparent power capacities for the construction/reinforcement of the substations. In this way, the binary variable $x_{s,h,t,u}^{sub}$ represents the option to construct/reinforce a substation using type t from initial type h (only transitions in which $t > h$ are allowed). Moreover, the substation types are sorted incrementally, according to the power capacity and the investment costs. Constraint (15) avoids the execution of more than one type of investment in the same stage (i.e., only one of the available power capacities can be chosen for construction/reinforcement), while (16) guarantees that a specific investment in a substation (from h to t) can be carried out only one time along the planning horizon. In addition, (17) establishes that the reinforcement of a substation using initial type h can be done only if that type was used to construct/reinforce the substation in previous stages. The binary parameter $\theta_{s,h}^{sub}$ represents the initial state of the substation at the beginning of the planning horizon, i.e., it is 1 if the substation was constructed and 0 otherwise. Finally, (18) guarantees that the operation of a substation is enabled only if the corresponding investment was carried out, while (19) allows for the operation of the substation using only one type of investment in each stage, following the same logic as (15) for the operation state.

$$\sum_h \sum_t x_{s,h,t,u}^{sub} \le 1 \ \forall s,u \tag{15}$$

$$\sum_u x_{s,h,t,u}^{sub} \le 1 \quad \forall s,h,t \tag{16}$$

$$x_{s,h,t,u}^{sub} \le \theta_{s,h}^{sub} + \sum_{k=1}^{u-1} \sum_r x_{s,r,h,k}^{sub} \quad \forall s,h,t,u \tag{17}$$

$$y_{s,t,u}^{sub} \le \theta_{s,t}^{sub} + \sum_{k=1}^{u} \sum_h x_{s,h,t,k}^{sub} \ \forall s,t,u \tag{18}$$

$$\sum_t y_{s,t,u}^{sub} \le 1 \quad \forall s,u \tag{19}$$

D. Logical Constraints Associated with Circuits

Constraints (20)-(24) enable the coordination of the investment and operation of the circuits along the planning horizon. This set of equations follows the same logical structure of the constraints related to the coordination of the investment and operation of the substations. The investment types correspond to the available current capacities for the construction/reinforcement of the circuits. In this way, the construction/reinforcement of a circuit using type b from initial type a is represented by the binary variable $x_{ij,a,b,u}^{cir}$ (only transitions in which $b > a$ are allowed). The operation of a circuit using type b is represented by the binary variable $y_{ij,b,u}^{cir}$, and the binary parameter $\theta_{ij,a}$ represents the initial state of the circuit at the beginning of the planning horizon, i.e., it is 1 if the circuit was constructed and 0 otherwise.

$$\sum_a \sum_b x_{ij,a,b,u}^{cir} \le 1 \quad \forall ij,u \tag{20}$$

$$\sum_u x_{ij,a,b,u}^{cir} \le 1 \quad \forall ij,a,b \tag{21}$$

$$x_{ij,a,b,u}^{cir} \le \theta_{ij,a}^{cir} + \sum_{k=1}^{u-1} \sum_c x_{ij,c,a,k}^{cir} \quad \forall ij,a,b,u \tag{22}$$

$$y_{ij,b,u}^{cir} \le \theta_{ij,b}^{cir} + \sum_{k=1}^{u} \sum_a x_{ij,a,b,u}^{cir} \quad \forall ij,b,u \tag{23}$$

$$\sum_b y_{ij,b,u}^{cir} \le 1 \quad \forall ij,u \tag{24}$$

E. Mathematical Modeling of EVCSs

The set of equations (25)-(28) used to model the EVCSs was developed according to the assumptions established in Section II. Constraint (25) guarantees that an EVCS can be allocated only one time in a node along the planning horizon. In addition, (26) allows the installation of chargers (considering the maximum number $\overline{C}_p$) only if an EVCS was already allocated. Constraint (27) limits the number of chargers operating in each stage such that they do not exceed the number of chargers already installed.

$$\sum_u x_{p,u}^{cs} \le 1 \quad \forall p \tag{25}$$

$$\sum_e \sum_{k=1}^{u} n_{p,e,k}^{chi} \le \overline{C}_p \sum_{k=1}^{u} x_{p,k}^{cs} \quad \forall p,u \tag{26}$$

$$n_{p,e,u}^{cho} \le \sum_{k=1}^{u} n_{p,e,k}^{chi} \quad \forall p,e,u \tag{27}$$

Equation (28) relates the number of EVs of type v that need to be charged ($N_{v,u}^{EV}$) with the number of EVs that are assigned to different charger types ($n_{e,v,u}^{ev}$). The term on the right-hand side of (28) is used to consider the stochastic behavior associated with the number of EVs, and it depends on the robustness factor $\phi(\varepsilon)$ corresponding to the area under a normal distribution curve for a confidence level of $1-\varepsilon$ and the standard deviation of the number of EVs ($\sigma_{v,u}^{EV}$). Moreover, (29) establishes that the energy that can be supplied by the chargers during their operating time dw^{cs} should satisfy the energy required by the EVs. It is written in terms of the rated power of the charger type e (P_e^{ch}), the energy required by an EV of type v (E_v^{req}), the difference between the maximum EV SOC (ϕ_{soc}^{max}), and a factor that represents the EV SOC at arrival (ϕ_{soc}).

$$\sum_e n_{e,v,u}^{ev} = N_{v,u}^{EV} + \phi(\varepsilon)\sigma_{v,u}^{EV} \quad \forall v,u \tag{28}$$

$$\sum_p P_e^{ch} n_{p,e,u}^{cho} dw^{cs} \ge \sum_v n_{e,v,u}^{ev} E_v^{req} (\phi_{soc}^{max} - \phi_{soc}) \quad \forall e,u \tag{29}$$

F. Chance Constraints for the Substation Capacity

Chance constrained programming is a type of robust programming that incorporates randomness in the model via a probabilistic measure over uncertain constraints [19]. The constraints, which contain stochastic parameters, are guaranteed to be satisfied with a certain probability at the optimum solution point. Thus, the chance constraint (30) considers the stochastic behavior of the conventional loads and EV demand, and it guarantees the fulfillment of the substation capacity within a determined confidence level. This constraint is written in terms of the stochastic apparent power supplied by the substation ($\widetilde{S}_{s,u}$), the capacity ($\overline{S}_t$), and the investment variables. It guarantees that the substation capacity is satisfied considering a robustness probability (related to the robustness parameter ε).

$$Prob\Big\{\widetilde{S}_{s,u} \leq \sum_t \overline{S}_t y^{sub}_{s,t,u}\Big\} \geq 1-\varepsilon \;\; \forall s,u \tag{30}$$

Chance constraint (30) can be represented by the linear constraint (31), as proposed in [19], in which $S_{s,u}$ and $\sigma_{s,u}$ are, respectively, the mean value and the standard deviation of the apparent power supplied by the substation.

$$S_{s,u} + \phi(\varepsilon)\sigma_{s,u} \leq \sum_t \overline{S}_t y^{sub}_{s,t,u} \quad \forall s,u \tag{31}$$

It is necessary to obtain an expression relating the uncertain load with the apparent power supplied by the substations. Since there is not an explicit relationship between the active power demand and the apparent power of the substation, and due to the nonlinear relationship between active, reactive, and apparent power (given by $S_{i,u} = \sqrt{{P^S_{s,u}}^2 + {Q^S_{s,u}}^2}$), the calculation of the mean and the standard deviation of $\widetilde{S}_{s,u}$ is complex. Therefore, these values are calculated by estimating the active power and assuming a power factor for the power supplied by the substation (ϕ_{pf}). For this purpose, the active power supplied by the substation can be expressed in terms of the uncertain demands ($\widetilde{P}^D_{i,u}$), the EV demand represented by the number of chargers ($n^{cho}_{i,e,u}$) with its corresponding rated power (P^{ch}_e), the power injected by the DG units, and the power losses, as shown in (32). Moreover, it is assumed that the power losses correspond to a percentage of the total active power supplied by the substation ($\%P^{loss}$).

$$\widetilde{S}_{s,u} = \sum_i \omega^{sub}_{s,i,u}\Big[(1+\%P^{loss})(\widetilde{P}^D_{i,u} + \sum_e n^{cho}_{i,e,u}P^{ch}_e) - \sum_g P^{DG}_{i,g,u}\Big]\phi^{-1}_{pf} \;\; \forall s,u \tag{32}$$

The binary variable $\omega^{sub}_{s,i,u}$ indicates whether the node i is connected to the substation s; it is obtained from the analytical formulation that finds the shortest path through a radial graph between each node and its corresponding source, as explained in [26].

Since it is assumed that the loads are independent normal variables, the mean value for the apparent power is obtained from (32) by taking the mean values of the demands, as shown in (33).

$$S_{s,u} = \sum_i \omega^{sub}_{s,i,u}\Big[(1+\%P^{loss})(P^D_{i,u} + \sum_e n^{cho}_{i,e,u}P^{ch}_e) - \sum_g P^{DG}_{i,g,u}\Big]\phi^{-1}_{pf} \;\; \forall s,u \tag{33}$$

On the other hand, the standard deviation for the apparent power is calculated by (34)-(35), considering that, for normal distribution functions, the variance of the apparent power ($\sigma^{sq}_{s,u}$) corresponds to the sum of the load variances (${\sigma^D_{i,u}}^2$) and that the variance ($\sigma^{sq}_{s,u}$) is the square of the standard deviation ($\sigma_{s,u}$), (approximated using the function f and a maximum value $\overline{\sigma}_{s,u}$).

$$\sigma^{sq}_{s,u} = \Big[(1+\%Ploss)\phi^{-1}_{pf}\Big]^2 \sum_i {\sigma^D_{i,u}}^2 \omega^{sub}_{s,i,u} \;\; \forall s,u \tag{34}$$

$$\sigma^{sq}_{s,u} = f\left(\sigma_{s,u}, \overline{\sigma}_{s,u}, \Gamma\right) \;\; \forall s,u \tag{35}$$

Thus, the proposed MILP model, described by (1)-(29), (31), and (33)-(35), is a robust formulation for the multi-stage joint expansion planning of EDSs and EVCSs, which considers the stochastic behavior of the conventional loads and EV demand. This MILP model can be solved using classical optimization techniques to find the optimal solution that guarantees the fulfillment of the substation capacity within a robustness level.

IV. Test and Results

The mathematical model described in section III was implemented in AMPL [21] and solved via CPLEX [22]. The application of the proposed model is illustrated using a didactic 18-node distribution system adapted from [9] and 54-node distribution system [27].

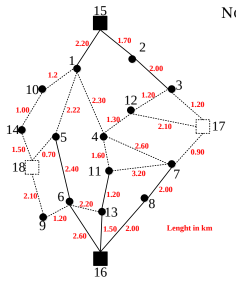
A. Expansion Planning for the 18-Node Distribution System

The didactic 18-node distribution system has 4 substations, 14 load nodes, and 26 circuits, and a nominal voltage of 20 kV. Two substations of type 1 are constructed in nodes 15 and 16 at the beginning of the planning horizon, as shown in Fig. 1. Furthermore, continuous lines represent constructed circuits, while dashed lines represent circuits for expansion and red numbers correspond to the circuit length. Three planning stages are considered, each one with a duration of 5 years; the load data for each stage is shown in Fig. 1.

Two substation types are available for this system, with capacities of 8 MVA and 12 MVA, while two circuit types are considered, with capacities of 197 A and 314 A [9], [20]. The construction and reinforcement costs of the substations and circuits are shown in Table I. The interest rate is defined as 10%. c^v_s is 0, i.e., the operational costs of the substations are neglected. One type of DG unit is considered, with a cost equal to $\$2200 \cdot 10^3$, a capacity of 3000 kVA, and a power factor of 0.95. The candidate nodes for allocating DG units are $\{1,3,7,8,9,10,11,12\}$, and a limit of 35% for the DG penetration is adopted. The capacitor allocation considers a limit of six CBs, with at most four modules per bank; parameters c^{cb}, c^{mod}, and Q^{esp}_{bc} are \$1000, \$900, and 300 kVAr, respectively.

TABLE I
SUBSTATION AND CIRCUIT COSTS (10^3\$)

	Substations Final type		Circuits Final type	
Initial type	1	2	1	2
0 (not build)	1000	1800	25	35
1	-	800	-	30



NOMINAL LOAD DATA (KVA)

Node	Stage 1	Stage 2	Stage 3
1	4050	4735	5420
2	780	995	1210
3	2580	3380	3980
4	320	410	490
5	280	370	470
6	1170	1305	1440
7	4040	4200	4360
8	720	830	940
9	0	1150	1350
10	0	3050	3160
11	1620	1620	2200
12	0	0	1220
13	2160	2160	2400
14	0	0	2100

Fig. 1. Initial Topology of the 18-node System

Two types of EVs are considered to represent the whole EV population: a Tesla and a Nissan Leaf, with battery capacities of 50 kWh and 25 kWh. Moreover, the factor ϕ_{soc} is assumed to be 0.5, based on the probability distribution function for the initial EV SOC presented in [28]. The EV penetration level, i.e., the percentage of users with an EV, is 2%, 11%, and 30% for each stage of the planning horizon [15]. It is also assumed that 20% of the EVs are charged at home, while the other 80% are charged in public EVCSs. Therefore, 210, 1688, and 5521 EVs along the three stages are charged in the EVCSs.

The installation cost of an EVCS, including the operational cost, is defined as c^{cs} = \$500 (the operational cost is considered to be 10% of the installation cost [29]). The operation time of the EVCSs is defined as 12 hours per day. The candidate nodes for allocating EVCSs are $\{3, 8, 9, 10, 11\}$. These locations should have suitable characteristics related to the space and support from nearby residents, as mentioned in [5]. Two types of chargers, denoted as FC (fast charger), with c_e^c = 60 US\$ and P_e^{ch} = 50 kW, and SC (slow charger), with c_e^c = 9 US\$ and P_e^{ch} = 10 kW, are used in the EVCSs [29], [30].

The results for the EDS expansion planning are analyzed considering a deterministic and robust approach. First, the proposed model is evaluated using deterministic values for the demands, i.e., the corresponding standard deviations are zero. Then, future uncertainties related to the demands are taken into account by the robust formulation.

1) Deterministic Approach: In order to analyze the multistage joint expansion planning of EDSs and EVCSs from a deterministic approach, two cases are evaluated: expansion planning without EVCSs (Case A) and expansion planning considering the allocation and sizing of EVCSs (Case B). In Case A, it is assumed that all of the EVs are charged in homes (i.e., home charging mode) at the peak hour, assuming the worst case for the EDS operation. Table II shows a summary of the investment and operational costs for each case. It can be noted that there is a positive impact on the EDS, due to the allocation of EVCSs. When the EV demand is distributed in each node of the EDS (i.e, Case A), the conventional load is increased, and additional investments are required to meet the total demand. Indeed, Case A presents higher investment costs in substations, circuits, and DG units, as well as in the the energy cost supplied by the substations and the DG units along the planning horizon. In Case B, wherein the EV demand is concentrated in some nodes of the system (i.e., EV charging in EVCSs), the investment and operational costs are reduced by 3.12% approximately, resulting in a positive impact for the EDS in comparison with Case A. The expansion plans for both cases are illustrated in Figs. 2 and 3 (topology in operation is shown). Note that, without EVCSs (Fig. 2), the substations at nodes 17 and 18 are constructed in Stage 3, and most of the circuits are built with higher capacity conductors.

TABLE II
SUMMARY INVESTMENT AND OPERATIONAL COSTS (10^3\$)

COST	Case A	Case B	Case C
IS	1,006.46	385.54	1,006.46
IC	397.74	355.32	339.11
ICB	21.79	23.39	24.22
IDG	7,462.42	5,766.03	5,766.03
ICS	0.00	2,324.73	2,875.22
EC	67,111.42	58,318.91	59,326.24
Total	75,999.83	67,173.91	69,337.29

TABLE III
NUMBER OF CHARGERS: DETERMINISTIC APPROACH

Stage	1		2		3	
Node	FC	SC	FC	SC	FC	SC
3	2	9	14	7	23	187
8	-	-	7	1	-	-
14	-	-	-	-	1	3
15	-	-	-	-	-	23
Total	2	9	21	8	24	213

In Case B, when EVCSs are considered, the topology of the network is different. Substation 17 is constructed in Stage 3, and different circuits are constructed/reinforced using, mostly, conductors with lower capacity (see Fig. 3). Furthermore, the allocation of the DG units and CBs is also different when the EVCSs are considered in the expansion planning. Only three DG units are installed in Stage 3 for Case B, while for Case A, five DG units are required in the same stage. The EVCSs are mainly allocated at nodes near the DG units and CBs, in an attempt to maintain a suitable operation of the EDS. For instance, one EVCS is located at node 3, along with a DG unit in Stage 1, and another EVCS and a CB are located at node 11 in Stage 3.

Table III shows the number of each type of charger allocated in each node and each stage for Case B. Four EVCSs and 277 chargers (47 FCs and 230 SCs) are necessary to meet the power demand of the EVs during the planning horizon.

Finally, it must be highlighted that, in both cases, some circuits are disconnected in order to maintain the radial operation of the EDS.

2) Robust Approach: The multistage joint expansion planning of the EDS and EVCSs is analyzed considering the stochastic behavior of the conventional loads and EV demand. Case B is extended, and the expansion planning, considering allocation and sizing of the EVCSs, is solved using the proposed robust formulation (Case C). It is assumed that the conventional load and the number of EVs follow a normal distribution. The mean values for the loads are the ones shown in Fig. 1, while the mean values for the number of EVs are the same as those in Case B. Moreover, the standard deviations are equal to 15% of the corresponding mean values.

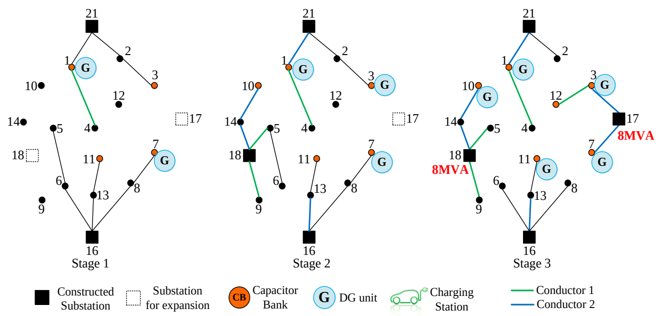


Fig. 2. Multistage EDS expansion planning for Case A.

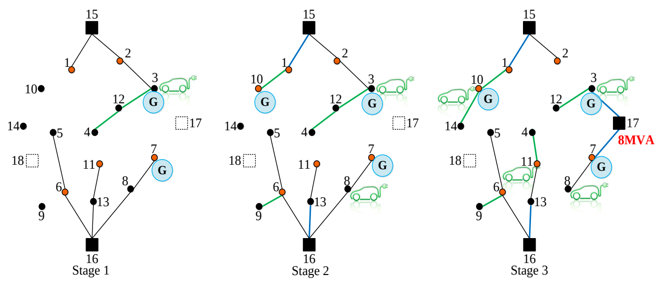


Fig. 3. Multistage EDS expansion planning for Case B.

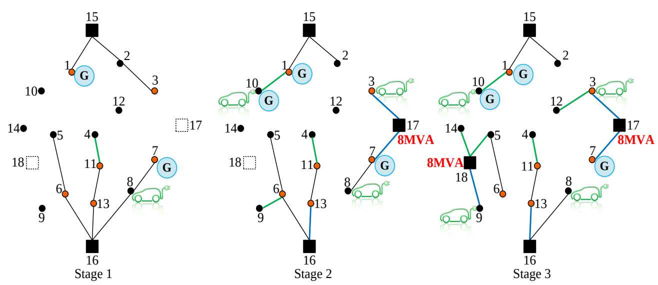


Fig. 4. Multistage EDS expansion planning for Case C.

The robustness parameter used in the chance constraint for the substation capacity and the estimation of the number of EVs is 5%, i.e., $\phi(\varepsilon)$ is equal to 1.645. This value guarantees the accomplishment of the substation capacity constraint with a probability of 95%. Furthermore, it covers 95% of the area under the normal distribution curve for the EV penetration.

The investment and operational costs for Case C are shown in Table II. It should be noted that the total cost of the robust solution is higher than the total cost of the deterministic solution (Case B), a difference of approximately 4%. This fact is due to the additional investments required to guarantee enough capacity of the substations, in order to account for uncertainties in the demand.

In Case C, two new substations are constructed along the planning horizon: Substations 17 and 18 in Stages 2 and 3, respectively (see Fig. 4). It must be highlighted that, in comparison with Case B, one additional substation should be built to avoid possible overloads related to demand growth that may be larger than expected. It should also be noted that the investments in the circuits and the topology of the EDS are different in comparison with Case B, i.e., circuits of higher capacities are used. For instance, conductors of type 2 are necessary to connect some EVCSs.

The allocation of DG units and CBs is also different along

TABLE IV
NUMBER OF CHARGERS: ROBUST APPROACH

Stage	1		2		3	
Node	FC	SC	FC	SC	FC	SC
3	-	-	6	-	-	52
8	3	8	2	-	16	41
13	-	-	-	-	3	214
14	-	-	20	1	2	6
Total	3	8	28	1	21	313

TABLE V
FAILURE RATE OF THE SUBSTATION CAPACITY (%)

	Stage 1				Stage 2				Stage 3			
Substation	15	16	17	18	15	16	17	18	15	16	17	18
Case B	0.0	0.2	-	-	3.9	67.9	-	-	43.8	36.6	0.4	-
Case C	0.0	1.4	-	-	0.0	0.0	0.2	-	0.0	2.6	2.2	1.0

the expansion horizon when uncertainty is considered. The CBs are allocated at the same nodes as in Case A. However, three DG units are allocated at nodes 1, 7, and 10. The allocation and sizing of the EVCSs for Case C are shown in Table IV. Four EVCSs with 374 chargers (52 FCs and 322 SCs) are necessary to meet the power demand of the EVs during the planning horizon. As in Case B, most of the EVCSs are allocated at nodes close to energy sources and CBs.

The results show that the expansion plans for the deterministic and robust approaches (Case B and C, respectively) are different in terms of the investment costs in substations, circuits, CBs, and EVCSs. Those costs are increased in order to provide a robust solution for the EDS expansion planning. In all cases, the results show changes in the topology of the network, in the reinforcement of circuits, and in the construction of new substations. These investments are proposed to satisfy the conventional loads and EV demand requirements.

Additionally, Monte Carlo simulations are carried out in order to evaluate the robustness of the expansion plan, considering the substation capacity. The simulations are made taking into account the normal distribution of the stochastic demands. Table V shows the failure rate of the substation capacity for Cases B and C at each stage of the planning horizon. The results obtained after 1,000 Monte Carlo simulations show that the deterministic approach (Case B) has the worst performance, with violations in the substation capacities, greater than 10%. Specifically, at node 16, the violation is higher than 65% in Stage 2 and almost 37% in Stage 3. Although the solution for Case C has a larger cost, the failure rate of the substation capacity is maintained below the limit defined by the robustness parameter, i.e., lower than 5%.

The results show that, considering only economic aspects, the best expansion plan is the one obtained using the deterministic approach, i.e., Case B. However, under uncertain conventional load and EV demand, this plan presents a large substation capacity failure rate. On the other hand, the more expensive investment plan, found by the robust approach (Case C), is robust enough to deal with the uncertainty associated with the demands.

B. Expansion Planning for the 54-Node Distribution System

An additional test using a 54-node distribution system, adapted from [27] was used in order to verify the scalability of the proposed mathematical model. It was verified that

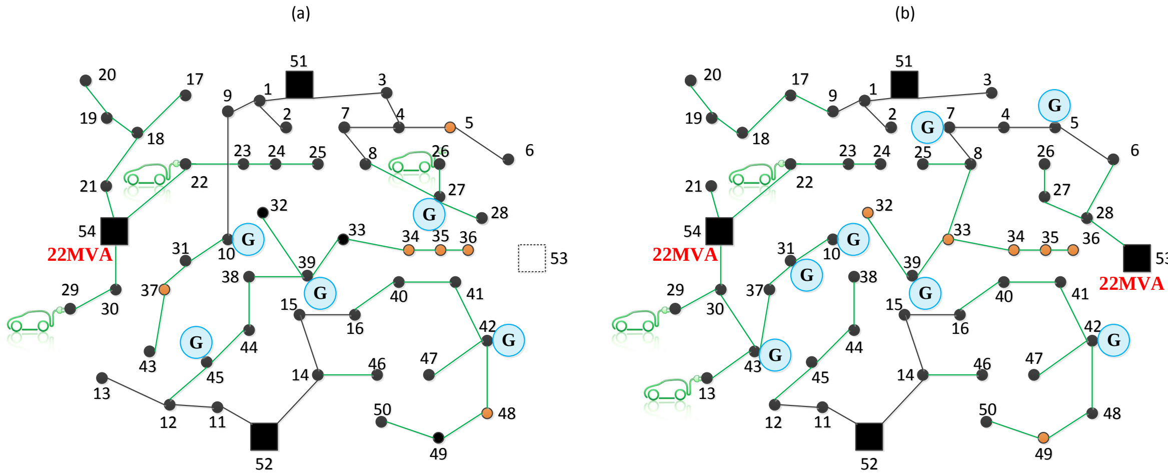


Fig. 5. Multistage EDS expansion planning for 54-node system at stage 3. a) Case B and b) Case C

the proposed model is able to solve the complex expansion planning for this distribution system. The results for the EDS expansion planning are analyzed considering the allocation and sizing of the EVCSs, i.e., Case B and Case C (the deterministic and robust approach, respectively).

The investment and operational costs for Case B and Case C are $83,156.71x10^3$ and $88,668.59x10^3$, respectively. As in the 18-node test system, it should be noted that the total cost of the robust solution is higher than the total cost of the deterministic solution (a difference of approximately 6%). This fact is due to the additional investments required to guarantee enough capacity of the substations to deal with the uncertainties in the demand. In Case B, Substation 54 is built in Stage 1, and different circuits are constructed using only one conductor type. Furthermore, only five DG units are installed in Stage 3 for Case B, while for Case C, seven DG units are required in the same stage (see Fig. 5). The EVCSs are mainly allocated at nodes near the DG units and CBs, in an attempt to maintain a suitable operation of the EDS. In Case C, two new substations are constructed along the planning horizon: Substations 54 and 53 in Stages 2 and 3, respectively. In comparison with Case B, one additional substation should be built to avoid possible technical problems caused by the unexpected demand growth.

The investments in the circuits and the topology of the EDS are also different for both cases. It must be highlighted that, in comparison with Case B, the investment in the circuits in Case C is also higher. The allocation of DG units and CBs, as well as the EVCSs, is also different along the expansion horizon when uncertainty is considered. For instance, three EVCSs with 792 SCs are necessary to meet the power demand of the EVs during the planning horizon in Case B, whereas in Case C, three EVCSs with 979 chargers (2 FCs and 977 SCs) are installed. As in the previous test, most of the EVCSs are allocated at nodes close to energy sources and CBs. In addition, the robustness of the expansion plan is evaluated for Case C through Monte Carlo simulations. Similar to the previous test system results, the failure rate of the substation capacity is maintained below the limit defined by the robustness parameter.

V. Conclusion

A novel mixed-integer linear programming (MILP) model for the robust multistage joint expansion planning problem of electrical distribution systems (EDS) and the allocation and sizing of Electric Vehicles Charging Stations (EVCSs) has been developed. The proposed formulation defines the construction/reinforcement of substations, EVCSs, and circuits, and the allocation of distributed generation units and capacitor banks. Chance constraints were used in the robust formulation to consider the uncertainties associated with the conventional loads and EV demand, guaranteeing the fulfillment of the substation capacity and the EV requirements within a specified confidence level.

The results demonstrate that the allocation of EVCSs results in a positive impact on the expansion plan for the EDS. The impact is mainly reflected by the differences between the substation and the circuit investments, as well as in the topology of the network. Thus, there is a reduction in the total cost of the investment plan when EVCSs are considered in the EDS expansion planning.

The solution provided by a deterministic approach, considering EVCSs, leads to more economic expansion plans. However, under uncertain conventional load and EV demand, it could present high failure rates for the substation capacity. On the other hand, the robust solution provides an investment plan with a larger cost, but it is robust enough to deal with the uncertainty associated with the demands.

In this way, the decision-maker can choose an expansion plan according to a given risk level associated with the demand variations in the EDS operation.

Monte Carlo simulations were carried out in order to verify the compliance of the proposed chance constraint in the robust formulation. It was found that the proposed robust formulation provides a solution in which the substation capacity and the EV requirements are satisfied within a specified confidence level.

APPENDIX

A piecewise approximation is used to define a function f, which calculates the square value of a variable ρ, limited by the interval $[0, \bar{\rho}]$. If the interval is partitioned into Γ equally sized blocks, the partition set $\mathcal{P} = \{0, \bar{\rho}/\Gamma, 2\bar{\rho}/\Gamma, \ldots, \bar{\rho}\}$ would be defined so that every block would have an equal length of $\bar{\rho}/\Gamma$. Considering that $\Delta_{\rho,\gamma}$ is a continuous variable that defines the value of the n-th block in partition $\mathcal{P}$, the piecewise linear approximation of ρ^2 is given by (36)-(40). This type of function has a general structure, as follows:

$$f(\rho, \bar{\rho}, \Gamma) = \sum_{\gamma=1}^{\Gamma} m_{\rho,\gamma} \Delta_{\rho,\gamma} \tag{36}$$

$$\rho^+ - \rho^- = \rho \tag{37}$$

$$\rho^+ + \rho^- = \sum_{\gamma=1}^{\Gamma} \Delta_{\rho,\gamma} \tag{38}$$

$$0 \leq \Delta_{\rho,\gamma} \leq \bar{\rho}/\Gamma \quad \forall \gamma = 1, .., \Gamma \tag{39}$$

$$m_{\rho,\gamma} = (2\gamma - 1)/\Gamma \quad \forall \gamma = 1, .., \Gamma \tag{40}$$

where Γ is the number of discretizations used in the function f; $m_{\rho,\gamma}$ is the slope of the γth block of the piecewise discretization of ρ; $\Delta_{\rho,\gamma}$ is the value of the γth auxiliary variable used in the discretization of ρ; and ρ^+ and ρ^- are positive auxiliary variables used in the calculation of $|\rho|$.

REFERENCES

[1] H. Bulkeley, M. Paterson, and J. Stripple, *Towards a Cultural Politics of Climate Change: Devices, Desires and Dissent*. Cambridge University Press, 2016.

[2] M. C. Falvo, D. Sbordone, I. S. Bayram, and M. Devetsikiotis, "EV charging stations and modes: International standards," in *Int. Symp. Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), 2014*, June 2014, pp. 1134–1139.

[3] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 371–380, Feb. 2010.

[4] P. S. Georgilakis and N. D. Hatziargyriou, "A review of power distribution planning in the modern power systems era: Models, methods and future research," *Elec. Power. Syst. Research*, vol. 121, pp. 89–100, 2015.

[5] Y. Zheng, Z. Y. Dong, Y. Xu, K. Meng, J. H. Zhao, and J. Qiu, "Electric vehicle battery charging/swap stations in distribution systems: Comparison study and optimal planning," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 221–229, Jan. 2014.

[6] Z. Hu and Y. Song, "Distribution network expansion planning with optimal siting and sizing of electric vehicle charging stations," in *47th Int. Conf. Universities Power Eng. (UPEC), 2012*, Sep. 2012, pp. 1–6.

[7] W. Yao, J. Zhao, F. Wen, Z. Dong, Y. Xue, Y. Xu, and K. Meng, "A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems," *IEEE Transactions on Power Systems*, vol. 29, no. 4, pp. 1811–1821, July 2014.

[8] S. Wang, Y. Xu, Z. Y. Dong, J. Zhao, W. Yao, F. Luo, and Y. Wang, "A stochastic collaborative planning approach for electric vehicle charging stations and power distribution system," in *2016 IEEE Power and Energy Society General Meeting (PESGM)*, July 2016, pp. 1–5.

[9] A. Tabares, J. Franco, M. Lavorato, and M. Rider, "Multistage long-term expansion planning of electrical distribution systems considering multiple alternatives," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 1900–1914, May 2016.

[10] N. Neyestani, M. Damavandi, M. Shafie-khah, J. Contreras, and J. Catalao, "Allocation of plug-in vehicles' parking lots in distribution systems considering network-constrained objectives," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2643–2656, Sep. 2015.

[11] Z. Liu, F. Wen, and G. Ledwich, "Optimal planning of electric-vehicle charging stations in distribution systems," *IEEE Trans. Power Del.*, vol. 28, no. 1, pp. 102–110, Jan. 2013.

[12] M. Moradijoz, M. P. Moghaddam, M. Haghifam, and E. Alishahi, "A multi-objective optimization problem for allocating parking lots in a distribution network," *Int. J. Elect. Power & Energy Syst.*, vol. 46, pp. 115–122, 2013.

[13] F. Fazelpour, M. Vafaeipour, O. Rahbari, and M. A. Rosen, "Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics," *Energy Conversion and Manage*, vol. 77, pp. 250–261, 2014.

[14] M. Amini and A. Islam, "Allocation of electric vehicles' parking lots in distribution network," in *IEEE PES Conf. Innovative Smart Grid Technologies (ISGT), 2014*, Feb. 2014, pp. 1–5.

[15] I. Frade, A. Ribeiro, G. Gonçalves, and A. Antunes, "Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal," *Transportation Research Record: J. Transportation Research Board*, vol. 2252, no. 12, pp. 91–98, 2011.

[16] L. Zi-fa, Z. Wei, J. Xing, and L. Ke, "Optimal planning of charging station for electric vehicle based on particle swarm optimization," in *IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), 2012*, May 2012, pp. 1–5.

[17] E. Pashajavid and M. A. Golkar, "Optimal placement and sizing of plug in electric vehicles charging stations within distribution networks with high penetration of photovoltaic panels," *J. Renewable and Sustain. Energy*, vol. 5, no. 5, 2013.

[18] S. Guo and H. Zhao, "Optimal site selection of electric vehicle charging station by using fuzzy topsis based on sustainability perspective," *Applied Energy*, vol. 158, pp. 390 – 402, 2015.

[19] A. Charnes and W. Cooper, "Deterministic equivalents for optimizing and satisficing under chance constraints," *Operations Research*, vol. 11, no. 1, pp. 18–39, Jan. 1963.

[20] J. Franco, M. Rider, and R. Romero, "Robust multi-stage substation expansion planning considering stochastic demand," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 2125–2134, May 2016.

[21] R. Fourer, D. M. Gay, and B. W. Kernighan, *AMPL: A modeling language for mathematical programming*, 2nd ed. Pacific Grove, CA: Brooks/Cole-Thomson Learning, 2003.

[22] *CPLEX Optimization subroutine library guide and reference*, CPLEX division ed., ILOG Inc., Incline Village, NV, 2008.

[23] Z. Liu, F. Wen, and G. Ledwich, "Optimal siting and sizing of distributed generators in distribution systems considering uncertainties," *IEEE Trans. Power Del.*, vol. 26, no. 4, pp. 2541–2551, Oct. 2011.

[24] S. Miloca, N. Volpi, J. Yuan, and C. Pinto, "Expansion planning problem in distribution systems with reliability evaluation: An application in real network using georeferenced database," *Int. J. Elect. Power & Energy Syst.*, vol. 70, pp. 9 – 16, 2015.

[25] H. Xing, H. Cheng, L. Zhang, S. Zhang, and Y. Zhang, "Second-order cone model for active distribution network expansion planning," in *2015 IEEE Power Energy Society General Meeting*, July 2015, pp. 1–5.

[26] J. C. López, M. Lavorato, J. F. Franco, and M. J. Rider, "Robust optimisation applied to the reconfiguration of distribution systems with reliability constraints," *IET Gener., Transm., Distrib*, vol. 10, no. 4, pp. 917–927, 2016.

[27] M. Lavorato, M. J. Rider, A. V. Garcia, and R. Romero, "A constructive heuristic algorithm for distribution system planning," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1734–1742, Aug 2010.

[28] J. Quirós-Tortós, L. F. Ochoa, and B. Lees, "A statistical analysis of EV charging behavior in the UK," in *2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM)*, Oct. 2015, pp. 445–449.

[29] *How much do public and home EV charging stations really cost?*, Inside EVs. [Online]. Available: http://insideevs.com/how-much-do-public-and-home-ev-charging-stations-really-cost/

[30] *Model charging*, Tesla Motors. [Online]. Available: http://www.teslamotors.com/models-charging#/basics

Metaheuristic Optimization Algorithms for the Optimal Coordination of Plug-In Electric Vehicle Charging in Distribution Systems with Distributed Generation

Nataly Bañol Arias, John F. Franco, Marina Lavorato and Rubén Romero

Nataly Bañol Arias, John F. Franco and Rubén Romero are with the UNESP – Universidade Estadual Paulista, Faculdade de Engenharia de Ilha Solteira, Departamento de Engenharia Elétrica, Ilha Solteira, São Paulo, Brazil.

Marina Lavorato is with the UNICAMP – School of Applied Sciences, University of Campinas, Limeira, São Paulo, Brazil.

Postal address: Dra. Marina Lavorato de Oliveira
UNICAMP - University of Campinas
School of Applied Sciences
Limeira - SP Brazil

emails: {natycanta, jffranco, mlavorato}@gmail.com,
and ruben@dee.feis.unesp.br

Abstract

This paper proposes three metaheuristic optimization techniques to solve the plug-in electric vehicle (PEV) charging coordination problem in electrical distribution systems (EDSs). Optimization algorithms based on tabu search, greedy randomized adaptive search procedure, and a novel hybrid optimization algorithm are developed with the objective of minimizing the total operational costs of the EDS, considering the impact of charging the electric vehicle batteries during a specific time period. The proposed methodologies determine a charging schedule for the electric vehicle batteries considering priorities according to the PEV owners charging preferences. A 449-node system with two distributed generation units was used to demonstrate the efficiency of the proposed methodologies, taking into account different PEV penetration levels. The results show that the charging schedule found makes the economic operation of the EDS possible, while satisfying operational and priority constraints.

Keywords: Electrical distribution system, hybrid algorithm, metaheuristic, plug-in electric vehicle charging coordination.

1. Introduction

The future large-scale penetration of plug-in electric vehicles (PEVs) will bring both positive and negative consequences, depending on different points of view [1]. In the environmental context, PEVs reduce greenhouse gas emissions (CO_2,SO_2, and NO_x) by decreasing fossil fuel consumption [2]. On the other hand, PEVs benefit the transportation sector by providing low operational costs [3]. However, from the point of view of the electrical distribution system (EDS) operation, PEVs represent a significant new load that must be supplied efficiently by the system, fulfilling the final consumers needs [1]. Previous works have shown that the EDS operation is strongly affected when PEV charging is not properly coordinated [4]. Several problems, such as higher load peak, decrease in service quality, degradation of the voltage profile, overload of circuits, and increase in energy losses are consequences of PEV penetration [4]-[6]. Nevertheless, those impacts can be mitigated by using heuristic procedures to solve the PEV charging coordination (PEVCC) problem [4], [7], [8]-[10]. Charging strategies based on quadratic optimization models [6], [11] and mixed-integer linear programming (MILP) [12], [13] have been proposed. An MILP approach that minimizes the total daily cost due to EV charging to define the charging schedule in real-time was proposed in [13]. Other approaches based on decentralized PEV charging strategies have been investigated in [13], [14], [15]. In these latter works, each PEV is allowed to determine its own charging pattern, i.e., there is no central operator deciding when and at what rate each individual PEV will be charged.

On the other hand, centralized approaches have been considered for the PEVCC problem [10], [16], [17]. An algorithm for real-time smart load management applied to the PEVCC problem, which minimizes the total generation cost and the energy losses of the network, was developed in [10]. Furthermore, an evolutionary algorithm [16] and a metaheuristic method based on particle swarm optimization, genetic algorithms, and simulated annealing [17] were developed in order to provide quality solutions for the PEVCC problem.

The operation of the EDS, considering PEV charging and integration of DG sources, is a challenge for the EDS operator. Some authors have addressed this subject [8], [10], [18], [19]. Reference [18] proposed an online fuzzy coordination algorithm for the PEVCC problem that minimizes the total cost of energy generation and power losses, while maintaining the network's operational constraints and considering priority charging and DG resources. An optimization methodology for designing integrated PEV charging systems with multiple chargers, renewable DG, and storage units was proposed in [19].

Some other studies have considered the relationship between PEV charging and photovoltaic (PV) generation [20], [21], [22], as well as the relationship between PEV charging and wind power generation [23], [24]. Likewise, the PEVCC problem including DG operation in a three-phase generic LV distribution network was investigated in [25]. The management of DG units, demand response, and electric vehicles with V2G technology in a smart grid environment were considered in an optimization approach based on simulating annealing (SA) in [26]; additionally, a methodology based on mixed-integer nonlinear programming (MINLP) was proposed to compare the results obtained with the SA approach, showing an important reduction in the computational times.

1.1. Contributions

As discussed in [18], global optimization techniques can be used to solve the PEVCC problem, although these techniques require a large computational effort. For this reason, the application of alternative optimization techniques, such as metaheuristics, should be investigated. This work proposes novel optimization algorithms based on the metaheuristics Tabu Search (TS) [27] and Greedy Randomized Adaptive Search Procedure (GRASP) [28], to minimize the total operational costs of the EDS by finding the best possible PEV charging schedule that satisfies the PEV energy requirements, the priority charging conditions of the PEVs, and the operational constraints of the EDS. Also, a hybrid algorithm that, improves on the solutions found using the classical TS and GRASP algorithms is proposed. The performance of the proposed optimization methods was investigated in a 449-node EDS including medium and low voltage feeders.

The main contributions of this paper are as follows:

1. Novel metaheuristic algorithms for solving the PEVCC problem in EDSs, considering DG units, as well as the electrical and operational constraints of the system;

2. A procedure to obtain a suitable charging schedule for the PEVs with efficient computational behavior, which uses a sensitivity index for the variation of the energy costs related to the PEV charging.

2. Mathematical Formulation of the PEVCC problem

The PEVCC problem can be formulated as an MINLP model in which the steady-state operation of the EDS is modeled based on [29] and [30]. The solution of this model provides the optimal charging schedule for the PEV batteries. In order to model the PEVCC problem, the following assumptions are considered:

1. The PEV batteries must be charged in a defined time period divided in time intervals, in which the charging process is executed;

2. The energy required by each PEV battery is known at the beginning of the time period;

3. The EDS operator controls the PEV charging process, i.e., the PEVs are equipped with communication devices that make it possible to control their charging state in each time interval;

4. Additionally, in each state of the charging schedule the operational constraints of the EDS must be satisfied.

2.1. Objective Function

The main objective of the PEVCC problem is to minimize the total operational cost of the EDS (1). The objective function proposed in this work is formed by six components, calculated over the time period as the sum of the energy loss cost (2), the cost of energy consumption by the conventional loads, the PEVs, and energy provided by the DG units (3), a term that encourages the charging of PEVs with priority conditions (4), the penalization of voltage limit violations (5), the penalization of current limit violations (6), and a penalization associated with non-charged PEV energy (7). The cost represented in (4) enables PEV charging with priority conditions, where ρ_t is a decreasing function defined by the equation $2^{[6+24H(t-18)-t]}$, and $H\left(t\right)$ is a Heaviside function. This term encourages the charging of priority PEVs as soon as possible over the charging of non-priority PEVs.

$$\min \quad \omega + \beta + \gamma + \delta + \varphi + \psi \tag{1}$$

Where:

$$\omega = \sum_{t \in T} \mu_t \Delta_t \sum_{ij \in L} R_{ij} I_{ij,t}^2 \quad \forall ij \in L, \forall t \in T \tag{2}$$

$$\beta = \sum_{t \in T} \mu_t \Delta_t \sum_{j \in N} \left(P_{j,t}^d + P_{j,t}^v \right) + \eta \sum_{t \in T} \Delta_t \sum_{j \in N} P_{j,t}^g \quad \forall j \in N, \forall t \in T \tag{3}$$

$$\gamma = - \sum_{j \in N} \sum_{t \in T} \kappa_j \rho_t P_{j,t}^v \quad \forall j \in N, \forall t \in T \tag{4}$$

$$\delta = \theta \sum_{j \in N} \max[(\; - V_j) \, , 0]^2 \quad \forall j \in N \tag{5}$$

$$\varphi = \sigma \sum_{ij \in L} \max \left[\left(I_{ij} - \bar{I}_{ij} \right) , 0 \right]^2 \quad \forall ij \in L \tag{6}$$

$$\psi = \Pi \sum_{j \in N} \pi_j \quad \forall j \in N \tag{7}$$

2.2. Network Constraints

Three types of constraints are considered in the proposed model:

- Active and reactive power balance constraints along with the voltage drop in the circuits, which represent

Kirchhoffs laws and make it possible to calculate the steady-state operation of the EDS.

$$\sum_{ij \in L} P_{ij,t} - \sum_{kj \in L} \left(P_{kj,t} + R_{kj,t} I_{kj,t}^2\right) + P_{j,t}^g = P_{j,t}^d + P_{j,t}^v \quad \forall j \in N, \forall t \in T \tag{8}$$

$$\sum_{ij \in L} Q_{ij,t} - \sum_{kj \in L} \left(Q_{kj,t} + X_{kj,t} I_{kj,t}^2\right) + Q_{j,t}^g = Q_{j,t}^d \quad \forall j \in N, \forall t \in T \tag{9}$$

$$V_{i,t}^2 - V_{j,t}^2 = 2\left(R_{ij} P_{ij,t} + X_{ij} Q_{ij,t}\right) + Z_{ij}^2 I_{ij,t}^2 \quad \forall ij \in L, \forall t \in T \tag{10}$$

$$V_{j,t}^2 I_{ij,t}^2 = P_{ij,t}^2 + Q_{ij,t}^2 \quad \forall ij \in L, \forall t \in T \tag{11}$$

Equations (8) and (9) represent the active and reactive power balance and guarantee that all loads are supplied. Equations (10) and (11) represent the application of Kirchhoff's voltage law [31].

- Operational constraints such as voltage limits, current capacity, and DG limits.

$$0 \le P_{j,t}^g \le \bar{P}_j^g \quad \forall j \in N, t \in T \tag{12}$$

$${}_{j}^{g} \le Q_{j,t}^g \le \bar{Q}_j^g \quad \forall j \in N, t \in T \tag{13}$$

$$\left|Q_{j,t}^g\right| \le P_{j,t}^g \tan\left(\text{arcos}\left(pf_j\right)\right) \quad \forall j \in N, t \in T \tag{14}$$

Constraints (12)-(14) represent the operational limits of the DG units, taking into account that these constraints only appear for nodes with DG, and not substation nodes. The voltage limits and current capacity constraints are not presented individually because they are treated as penalizations in the objective function (1).

- Constraints associated with the PEVs: energy balance in the batteries, PEV maximum power consumption, and priority conditions.

$$E_j^v = \sum_{t \in T} \Delta_t P_{j,t}^v + \pi_j \quad \forall j \in N \tag{15}$$

$$P_{j,t}^v = \bar{P}^v x_{j,t}^v \quad \forall j \in N, t \in T \tag{16}$$

Equation (15) represents the energy balance of a PEV battery, which is expressed in terms of the energy charged in the battery (E_j^v), the power consumed in each time interval ($P_{j,t}^v$), and the energy not charged in the battery at the end of the time period (π_j). Equation (16) determines the power demanded by a PEV according to the maximum power of the PEV battery and its charging state (where $x_{j,t}^v$ is 1 if the battery is totally charged, otherwise, $x_{j,t}^v$ is 0).

The optimization model (1)-(16) is an MINLP due to the nonlinearities in (11). This kind of model can be linearized using different techniques, as presented in [30], in order to solve the problem more easily. Nevertheless, classical optimization techniques could present performance issues when the problem has large dimensions. As a result, it might be difficult to solve the problem in reasonable computational time. On the other hand, heuristic and metaheuristic techniques can provide good-quality solutions that are close to the optimal solution or even the optimal solution with less computational effort, which makes them suitable for solving the PEVCC problem.

3. Metaheuristic Optimization Algorithms for the PEV Charging Coordination Problem

New optimization algorithms based on TS and GRASP are presented in this section to solve the PEVCC problem. These algorithms have been developed to solve the PEVCC problem in EDSs and to minimize the total operational costs defined by (1). Additionally, a hybrid algorithm that combines TS and GRASP is developed.

In order to assess the steady-state operation of the EDS, including PEV charging and DG source operation, a specialized radial load flow based on the backward/forward load flow proposed in [32] is used. All loads are represented as constant active and reactive power loads.

3.1. Tabu Search Algorithm for the PEVCC

As any local search method, TS employs four basic components [30]:

1. A codification structure that represents a solution proposal and defines the search space;
2. A procedure to generate an initial solution;
3. A neighborhood structure to generate a subset of solutions;
4. A transition mechanism that establishes how to pass from a solution proposal to a new solution.

3.1.1. Codification structure

A solution proposal is represented in a matrix in which each row corresponds to a PEV and the number of columns is defined as the maximum number of time intervals required to charge the PEV batteries, as given by (17).

$$\lambda = \frac{E_j^v}{\bar{P}^v \Delta_t} \tag{17}$$

As illustrated in Fig. 1, the elements of the codification matrix are integer numbers that belong to the set of time intervals T and represent the time interval in which the PEV batteries are charged. In this way, the number 1 represents the time interval between 18:00 and 19:00, the number 2 represents the time interval between 19:00 and 20:00, and so on. For a given PEV, the chosen codification indicates the time intervals in which the PEV battery is charged; however, it does not necessarily indicate the sequence in which the PEV battery is charged. Fig. 1. illustrates the case in which three time intervals are needed to charge the PEVs ($\lambda = 3$).

Figure 1 goes here.

3.1.2. Initial Solution

As the energy costs could change over the time intervals, an initial solution can be built by charging the PEV batteries without priority conditions during the time intervals with the lower energy costs. In this case, usually the chosen time intervals are in the early morning. On the other hand, the charging of PEVs with priority conditions should be carried out during the first hours of the time period because it is expected that these PEVs need to be charged as soon as possible. So, following these conditions, the initial solution is easy to be generated. However, voltage and current limit violations may appear due to the simultaneous charging of the PEVs. If necessary, the optimization process can search in the solution space to eliminate such infeasibilities and find a good-quality solution. The proposed initial solution simulates an uncoordinated charging process in which the PEVs are connected to the network without being managed by the EDS operator. The proposed methodology allows the EDS operator to identify suitable time intervals to charge the PEVs.

3.1.3. Neighborhood structure

For a given solution proposal, a neighbor solution can be generated by changing the time intervals stored in one position of the codification matrix. That operation can be carried out for each row of the matrix (associated with a PEV) and for each column (associated with a charging time interval), with the condition that the new generated time interval differ from the current time intervals present in the selected row. Additionally, the new time interval must belong to the set of time intervals T. Thus, the feasibility of the new solution proposal is maintained from the point of view of the codification.

3.1.4. Transition mechanism

After evaluating all the neighbor solutions for a current configuration, a solution is chosen by applying the TS criteria and using a short-term memory structure, as explained in [27].

3.1.5. Steps of the tabu search algorithm:

Step 1: Generate the initial solution.

Step 2: Evaluate the neighborhood.

Step 3: Select the solution according to the TS transition mechanism.

Step 4: Update the TS short-term memory structure.

Step 5: Verify the stopping criterion. If it is satisfied, stop. Otherwise, return to Step 2.

3.2. GRASP Algorithm for the PEVCC

The GRASP algorithm is used to solve the PEVCC problem by adapting its construction and local search phases [28]. The codification of the solution proposal is presented in Section 3.1.1.

3.2.1. Construction phase

In the construction phase, an initial solution is iteratively formed by selecting one element at a time. The construction phase begins with an empty initial solution and, in each iteration, a PEV is chosen to be charged in a specific time interval. The process stops when λ time intervals have been assigned to all PEVs, i.e., all the periods required to charge the battery of each PEV in the system have been assigned. In each iteration of the construction phase, the next element to be added is selected from a Restrict Candidates List (RCL), which is built using a sensitivity index (18) and parameter $\alpha \in [0, 1]$. The sensitivity index $\Phi_{k,t}$ estimates, in each iteration, the variation of the objective function when the charging of a new element is considered, e.g., the k-th PEV at the t-th time interval. The use of this index to evaluate the objective function avoids the calculation of a complete load flow for all possible candidates.

$$\Phi_{k,t} = \mu_t \Delta_t \Delta P_{k,t}^{Loss} + \mu_t \Delta_t \bar{P}^v - \kappa_n \rho_t P_{k,t}^v \tag{18}$$

Thus, the sensitivity index improves the efficiency of the algorithm by reducing required computational effort. Using the sensitivity index, the RCL is defined by (19).

$$RCL = \{k, t \in X | \Phi_{min} \leq \Phi_{k,t} \leq \Phi_{min} + \alpha \left(\Phi_{max} - \Phi_{min} \right) \} \tag{19}$$

Where X is the set of index that represent the elements allowed to be added to the solution. Φ_{min} and Φ_{max} are the minimum and the maximum values for the index. The objective of (19) is to select the elements with the lowest values of $\Phi_{k,t}$. The value of α is adjusted experimentally by doing simulations with different values.

When the RCL is created, an element is chosen using a linear probability distribution function described in (20), where r_i represents the position of element i in the sorted RCL, according to the quality of $\Phi_{k,t}$. Therefore, the probability of choosing element i is found using (21).

$$b_i = 1/r_i \tag{20}$$

$$p_i = \frac{b_i}{\sum\limits_{j \in RCL} b_j} \tag{21}$$

The selection of the i-*th* element is implemented using a random number generator and a proportional selection criterion. The selected element is added to the solution in construction, and then, the objective function is calculated again using (1). This iterative process ends when a solution has been completely constructed. The construction phase of the proposed GRASP algorithm is comprised of the following steps:

Step 1: Read the input data and set α.

Step 2: Define an empty set as the initial solution, i.e., the EDS with no PEVs connected to the network. Calculate the steady-state operation of the EDS without PEVs.

Step 3: Calculate $\Phi_{k,t}$ using (18) for all the PEVs in all time intervals $t \in T$, which have not yet been added to the solution.

Step 4: Create the RCL using (19).

Step 5: Calculate p_i for all elements of the RCL and choose the element that will be added to the solution in construction.

Step 6: Evaluate the objective function.

Step 7: Check the stopping criterion. If it is satisfied, stop. Otherwise, return to step 3.

3.2.2. Local search phase

The main objective of the local search phase is to improve the solution obtained in the construction phase. A steep descent heuristic algorithm is implemented using the neighborhood structure proposed in

Section 3.1.3. After all the neighbors have been evaluated, the next solution will be the best neighbor solution found.

The local improvement process ends when none of the neighbor solutions are better than the current solution. The local search phase of the proposed GRASP algorithm has the following steps:

Step 1: Read the current solution found in the constructive phase of the GRASP algorithm.

Step 2: Generate a neighbor solution.

Step 3: Evaluate the objective function.

Step 4: If the neighbor solution is better than the current solution, make the transition to the neighbor solution.

Step 5: Check the stopping criterion. If there is no neighbor solution better than the current one, then the local search phase is finished. Otherwise, return to step 2.

3.2.3. Stopping criterion of the GRASP algorithm

The stopping criterion established in the GRASP algorithm is a maximum execution time. At the end of the process, when the maximum time is reached, the best found solution is the solution for the PEVCC problem.

3.3. Hybrid Optimization Algorithm (HOA)

Hybrid algorithms are frequently used to obtain good solutions for a certain problem by combining different search strategies from two or more methodologies in the solution space [34]. They are developed in order to improve the solutions found using simple algorithms. In this work, a novel hybrid optimization algorithm is proposed in order to improve the found solutions via the TS and GRASP methodologies previously presented.

The HOA takes advantage of the TS and GRASP characteristics. This way, the proposed HOA uses the GRASPs construction phase to generate a good-quality initial solution, and then the short-term strategies of the TS algorithm are applied in the local search phase. The HOA is an iterative process that, can be executed in a limited amount of time. Due to the features of GRASP, a different initial solution is generated in each iteration, making it possible to diversify the search process by exploring different regions of the search space. A flow chart of the proposed hybrid optimization algorithm is shown in Fig. 2.

Figure 2 goes here.

One advantage of the proposed HOA is its simple and practical application. Furthermore, the results demonstrate that the proposed HOA has better performance than the TS and GRASP methodologies, as shown in the results Section.

3.4. PEV Charging and DG Units

As mentioned in [35], DG units enhance the performance of the system, improving the voltage profiles and reducing the active power losses and total operational cost. Therefore, DG units were included in the optimization methodologies in order to identify their impact on the EDS operation and the scheduling of the PEV battery charging. Each methodology (TS, GRASP, and HOA) is used to define the optimal power injected by the DG units in each time interval. This optimization process consists of a unidimensional search, which makes small variations in the DG unit power, starting with an initial value, in order to improve the objective function.

4. Test and Results

The algorithms were developed in the programming language C++ and were executed using a Dell PowerEdge R910x64 computer with six processors at 1.87 HGz Model i7 4807. A 449-node distribution system was used to compare the performance of the TS, GRASP, and HOA methods. Four PEV charging scenarios, as shown in Table 1, were taken into account. In these scenarios, two PEV penetration levels were considered: 47% (198 PEVs) and 63% (264 PEVs). Additionally, it was assumed that some of the PEVs should be charged with priority. The 449-node system, whose data are available in [10], consisted of a network with 31 medium-voltage nodes (23kV) and 22 low-voltage feeders (415V), each with 19 nodes. The PEVs were connected in the low-voltage network.

The energy cost and the load for each time interval are available in [30]. The considered time period for the charging spanned from 18:00h until 08:00h, broken down into time intervals of 1 hour, i.e., $\Delta_t = 1h$. Therefore, time interval 1 was from 18:00h to 19:00h, time interval 2 was from 19:00h to 20:00h, and so on. The voltage limits for all cases were $\overline{V} = 0.9$pu and $\underline{V} = 1.0$pu, while the maximum current for all the low-voltage feeders was 200A.

Table 1 goes here.

There were two DG units connected at nodes 14 and 17, corresponding to a DG penetration of about 40% of the maximum demand. One of the DG units was a small hydro power plant with a fixed generation in each time interval. The other was a DG unit whose generation can vary over time depending on system requirements. The cost of the energy supplied by both DG units (η) was 0.04 $US\$/kWh$. The active and reactive power limits were $\bar{P}_n^g = 200$kW, $\bar{Q}_n^g = 100$kVAr, and $\underline{Q}_n^g = -100$kVAr with a fixed power factor equal to 0.9. The capacity of the PEV batteries was 20kWh, according to information provided in [33]. The maximum power of the battery was 4kW as assumed in [10].

With the purpose of maintaining a balance between a random and greedy selection in the GRASP and HOA algorithms, the alpha value chosen was $\alpha = 0.5$ for all scenarios. In order to investigate the performance of the proposed methodologies, tests considering time limits of 300, 600, and 1200 seconds were carried out. Moreover, an additional test considering a relatively large time limit (4h) was executed to study the convergence of the proposed methodologies. Table 2 shows the objective function value for each of the PEV charging scenarios for different time limits. In this table, it can be observed that, in most cases, the best objective function values were found using the HOA methodology. For this reason, the information presented about power consumption, minimum voltage, and power losses correspond to the results obtained using the HOA methodology. Note that there was little difference between the three proposed methodologies in terms of the value of the objective function. Table 3 shows the deviation of the objective function (in percentage) found by all methodologies for each PEV charging scenario relative to the best solution found in each case. The last row of the table contains the average deviation percentage for each case. The results show that all values corresponding to the HOA methodology had the smaller average deviation, close to zero, confirming that this methodology provides better solutions for the PEVCC problem.

Table 2 goes here.

Table 3 goes here.

The power consumption of the system (power generated by the substation and DG units) is shown in Figs. 3 and 4. The red areas represent the consumption of PEVs with priority conditions, the green areas represent the consumption of PEVs without priority conditions, and the white areas represent the conventional loads. As mentioned in Section 3.1.2, the initial solution proposed (uncoordinated charging) had low voltage problems and congestion in the feeders, as well as an increase in energy losses. Figs. 3 and 4 show that, after applying the proposed HOA, the power consumption of the system was modified to eliminate these infeasibilities.

Figure 3 goes here.

Figure 4 goes here.

The minimum voltages in each time interval are presented in Figs. 5 and 6. Figs. 5(a) and Fig.6(a) show that for cases A and B, the uncoordinated charging violated the voltage limits in the first five time intervals. A similar situation occurred for Cases C and D related to charging without priority conditions, as shown in Figs. 5(b) and Fig.6(b). In these cases, the uncoordinated charging violated the voltage limits in the last five time intervals due to the PEVs being charged in the periods with the lowest cost of energy. Note that after the application of the HOA methodology, the solutions found for all cases did not present any operational constraint violations. It is also possible to observe that the voltage profile improved with the use of DG units (Cases B and D).

Figure 5 goes here.

Figure 6 goes here.

The total energy losses of the EDS are presented in Fig. 7. The uncoordinated charging of the PEVs led to greater energy losses than with optimized charging. The solution found by the proposed HOA distributed the PEV charging adequately, avoiding an increase in the peak load and achieving a significant reduction in energy losses. Moreover, note that for Cases B and D, which considered DG units, the value of the total energy losses was smaller compared to the other cases.

Figure 7 goes here.

Table 4 shows a summary of the best objective functions and related costs for each charging scenario. The proposed HOA improved the operation of the distribution system by reducing the energy losses and eliminating the infeasibilities compared to uncoordinated charging. It is important to highlight that Cases A and B presented negative values for the objective function due to the term encouraging quick charging of the PEVs with priority conditions. For Cases C and D, the proposed HOA resulted in the charging of the PEV batteries in time intervals with lower energy costs. On the other hand, in Cases B and D considering DG units, the best objective functions were obtained because the cost of the energy generated by the DGs was lower.

Table 4 goes here.

The power injected by the DG units is shown in Fig. 8. Note that the DG units reached their maximum generation during the first time intervals available for PEV charging. This makes sense because, in these time intervals, the cost of the energy provided by the substation was greater than that of the energy generated by the DG units. Moreover, for Case B, which considered priority conditions, there was a concentration of the

PEV load in the same time intervals taking advantage of the DG operation. In Case D, which did not consider priority, a similar situation occurred, but with the difference that the DG units generated more power over the last time intervals due to the concentration of the PEV load in the time intervals with lower energy cost. In this case, the power generated by the DG units contributed eliminating the voltage and current violations, reducing the energy losses, and achieving an efficient system operation.

Figure 8 goes here.

5. Conclusions

Optimization algorithms based on Tabu Search, GRASP, and a novel hybrid optimization algorithm (HOA) were proposed in order to solve the Plug-in Electric Vehicle Charging Coordination (PEVCC) problem in electrical distribution systems. The results show that the proposed methodologies can be used to obtain the coordinated charging of PEV batteries, while maintaining the economical operation of the distribution system and satisfying the operational and priority constraints.

The three methodologies achieved good-quality solutions for the PEVCC problem compared to the results from an uncoordinated charging scenario. However, after making a comparative analysis between the three proposed methodologies, it was concluded that although all found similar solutions, the HOA provided better results for the solution of the PEVCC problem.

The results demonstrate that the presence of Distributed Generation (DG) units benefits the charging of PEVs. The voltage profile and the energy losses of the system are improved after the application of the proposed methodologies.

The results obtained show that the proposed methodologies provide good-quality solutions for the PEVCC problem in low computational time. Therefore, they can be auxiliary tools in smart grid schemes for the control of future distribution systems.

6. Acknowledgments

This work was supported by the Brazilian institutions CAPES, CNPq and FAPESP.

7. References

[1] A. Ipakchi, and F. Albuyeh, "Grid of the future," Power and Energy Magazine, vol. 7, pp. 52-62, Mar.-Apr. 2009.

[2] W. Kempton, V. Udo, K. Huber, K. Komara, S. Letendre, S. Baker, D. Brunner and N. Pearre., "A test of Vehicle-to-Grid (V2G) for energy storage and frequency regulation in the PJM system", Newark, DE: 2008.

[3] IEA, April 2013. Global EV Outlook: Understanding the electric vehicle landscape to 2020. OECD/IEA, Paris.

[4] J. A. P. Lopes, F. J., and Soares, P. M. R. Almeida, "Integration of electric vehicles in the electric power system," Proc. IEEE, v.99, n.1, pp. 168-183, Jan. 2011.

[5] S. Lin, Z. He, T. Zang, and Q. Qian, "Impact of plug-in hybrid electric vehicles on distribution systems," Int. Conf Power Syst. Tech. (POWERCON), pp. 1-5, 24-28, Oct. 2010.

[6] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," IEEE Trans. Power Syst., vol. 25, no. 1, pp. 371380, Feb. 2010.

[7] E. Sortomme, M. M. Hindi, S. D. J. M. Pherson, and S. S. Venkata, "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," IEEE Trans. Smart Grid, v.2, n.1, pp. 198-205, Mar. 2011.

[8] C. Jin, J. Tang, and P. Ghosh, "Optimizing electric vehicle charging with energy storage in the electricity market," IEEE Trans. Smart Grid, vol.4, no.1, pp. 311-320, Mar. 2013.

[9] Z. Luo, Z. Hu, Y. Song, Z. Xu, and H. Lu, "Optimal coordination of plug-in electric vehicles in power grids with cost-benefit analysisPart I: enabling techniques," IEEE Trans. Power Syst., vol.28, no.4, pp. 3546-3555, Nov. 2013.

[10] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," IEEE Trans. Smart Grid, vol.2, no.3, pp. 456-467, Sep. 2011.

[11] O. Sundstroem, and C. Binding, "Flexible charging optimization for electric vehicles considering distribution grid constraints," IEEE Trans. Smart Grid, vol.3, no.1, pp. 26-37, Mar. 2012.

[12] K. Clement, E. Haesen, and J. Driesen, "Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids," in Proc. Power Syst. Conf. Expo., pp. 17, 2009.

[13] Lunci Hua, Jia Wang, and Chi Zhou, "Adaptive electric vehicle charging coordination on distribution network," IEEE Trans. Smart Grid, vol.5, no.6, pp. 2666-2675, Nov. 2014.

[14] Zhongjing Ma, D.S. Callaway, and I.A. Hiskens, "Decentralized charging control of large populations of plug-in electric vehicles," IEEE Trans. on Control Systems Technology, vol.21, no.1, pp. 67-78, Jan. 2013.

[15] W. Chao-Kai, C. Jung-Chieh, T. Jen-Hao, and T. Pangan, "Decentralized plug-in electric vehicle charging selection algorithm in power systems," IEEE Trans. Smart Grid, vol.3, no.4, pp. 1779-1789, Dec. 2012.

[16] S. Hutterer, F. Auinger, and M. Affenzeller, "Metaheuristic optimization of electric vehicle charging strategies in uncertain environment," in Int. Conf. Probabilistic Methods Applied to Power Systems. 2012.

[17] J. Yang, L. He, and S. Fu, "An improved PSO-based charging strategy of electric vehicles in electrical distribution grid," Applied Energy, vol. 128, pp. 82-92, Sep. 2014.

[18] A. Masoum, S. Deilami, A. Abu-Siada, and M. Masoum, "Fuzzy approach for online coordination of plug-in electric vehicle charging in smart grid," IEEE Trans. Sust. Energy, vol. 6, no.3, pp.1112-1121, Jul. 2015.

[19] S.J. Gunter, D.J Perreault, S. Suresh, and K.K. Afridi, "Methodology for the optimal design of PEV charging systems with multiple chargers and distributed resources," IEEE PES Innovative Smart Grid Technologies (ISGT), pp. 1-6, 24-27 Feb. 2013.

[20] S.Y. Derakhshandeh, A.S. Masoum, S. Deilami, M.A.S. Masoum, and M.E. Hamedani Golshan, "Coordination of generation scheduling with PEVs charging in industrial microgrids," IEEE Trans. Power Syst., vol.28, no.3, pp. 3451-3461, Aug. 2013.

[21] S. Shengnan, F. Jahanbakhsh, J.R. Aguero, and Le Xu, "Integration of PEVS and PV-DG in power distribution systems using distributed energy storage - Dynamic analyses," IEEE PES Innovative Smart Grid Technologies (ISGT), pp. 1-6, 24-27 Feb. 2013.

[22] J.M. Foster, G. Trevino, M. Kuss, and M.C. Caramanis, "Plug-in electric vehicle and voltage support for distributed solar: theory and application," IEEE Systems Journal, vol.7, no.4, pp. 881-888, Dec. 2013.

[23] H. Weihao, S. Chi, C. Zhe, B. Bak-Jensen, "Optimal Operation of Plug-In Electric Vehicles in Power Systems with High Wind Power Penetrations," IEEE Trans. Sust. Ener., vol.4, no.3, pp. 577-585, Jul. 2013.

[24] W. Ting, Y. Qiang, B. Zhejing, and Y. Wenjun, "Coordinated Energy Dispatching in Microgrid With Wind Power Generation and PEVS," IEEE Trans. Smart Grid, vol.4, no.3, pp. 1453-1463, Sep. 2013.

[25] P. Papadopoulos, S. Skarvelis-Kazakos, I. Grau, L.M. Cipcigan, and N. Jenkins, "Predicting Electric Vehicle impacts on residential distribution networks with Distributed Generation," in Proc. IEEE Veh. Power Propulsion Conf. (VPPC), pp. 1-5, 1-3 Sep. 2010.

[26] T. Sousa, H. Morais, Z. Vale, P. Faria, and J. Soares, "Intelligent energy resource management considering vehicle-to-grid: A Simulated Annealing approach," in IEEE Pow. & Ene. Society Gen. Meeting, 22-26 Jul. 2012.

[27] F. Glover, and M. Laguna, "Tabu search". Norwell: Kluwer Academic Publishers, 1997.

[28] T. A. Feo, and M. G. C. Resende, "Greedy randomized adaptive search procedures," Journal of global optimization, v. 6, n. 2, pp. 109-133, 1995.

[29] M. D. Galus, R. A. Waraich, and G. Andersson, "Predictive, distributed, hierarchical charging control of PHEVs in the distribution system of a large urban area incorporating a multi agent transportation simulation," in 17th Power Syst. Computation Conf., Stockholm, Sweden, 2011.

[30] J. F. Franco, M. J. Rider, and R. Romero, "An MILP model for the plug-in electric vehicle charging coordination problem in electrical distribution systems," IEEE Pow. & Ener Society Gen. Meeting, 27-31 Jul. 2014.

[31] R. R. Gonçalves, R. P. Alves, J. F Franco, and M. J. Rider, "Operation planning of electrical systems using a mixed integer linear model," Journal of Control, Aut. and Electrical Systems, vol.24, n.3, Jun. 2013.

[32] R. G. Cespedes, "New method for the analysis of distribution networks," IEEE Trans. Power Del, vol. 5, no. 1, pp. 391-396, Jan. 1990.

[33] Nissan Vehicles - Model specifications. [Online]. Avaliable: http://www.nissanusa.com/electric-cars/leaf/versions-pecs/version.sl.html.

[34] T. Frierich, J. He, N. Hebbinghaus, F. Neumann, and C. Witt, "Analyses of Simple Hybrid Algorithms for the Vertex Cover Problem," in 14th IEEE Congress on Evolutionary Computation, pp. 26142621, Piscataway, 2007.

[35] G. Pepermans, J. Driesen, D. Haeseldonckx, R. Belmans, and W. D'haeseleer, "Distributed generation: definition, benefits and issues," Energy Policy, v. 33, n. 6, pp. 787-798, Apr. 2005.

Appendix A

The notation used throughout this paper is reproduced below for quick reference.

Sets:

L Set of circuits.

N Set of nodes.

T Set of time intervals.

Parameters:

α Grasp parameter.

β Cost of energy consumption by the conventional loads, the PEVs, and energy provided by the Distributed Generation (DG) [$/kWh].

b_i Linear probability distribution function.

δ Penalization cost due to voltage limits violations.

Δ_t Duration of time interval t.

η Cost of the total energy provided by the DGs [$/kWh].

E_j^v Energy that must be charged to the PEV at node j [kW].

φ Penalization cost due to the current limit violations.

$\Phi_{k,t}$ Sensitivity index.

γ Component of the objective function to encourage the charging of PEVs.

$\bar{I}_{ij}$ Current capacity of circuit ij [A].

κ_j PEV with charging priority connected at node j.

λ Number of time intervals required to charge a PEV.

μ_t Energy price in time interval t.

ω Cost of the energy losses.

Π Penalization for unsupplied PEV energy.

p_i Probability of choosing an i-th element to form the sorted RCL.

$P^d_{i,t}$ Active power demanded at node i in time interval t [kW].

$\bar{P}^g_i$ Maximum active power of DG unit at node i [kW].

$\bar{P}^v$ Maximum power of the PEV batteries [kW].

pf_i Power factor limit of the DG at node i.

ψ Cost associated with the non-charged PEV energy [$/kWh].

$Q^d_{i,t}$ Reactive power demanded at node i in time interval t [kVAr].

$\bar{Q}^g_i$ Maximum reactive power of DG at node i [kVAr].

$\underline{Q}^g_i$ Minimum reactive power of DG at node i [kVAr].

r_i Position of the element i in the sorted RCL.

R_{ij} Resistance of circuit ij [Ω].

ρ_t Parameter used to encourage charging with priority.

σ Penalization factor due to the current limit violation.

σ_z Penalization factor due to the voltage limit violation.

$\underline{V}$ Minimum voltage magnitude [V].

$\bar{V}$ Maximum voltage magnitude [V].

X_{ij} Reactance of circuit ij [Ω].

Z_{ij} Impedance of circuit ij [Ω].

Variables:

$I_{ij,t}$ Current magnitude in circuit ij in time interval t [A].

π_i PEVs uncharged energy [kW].

$P_{ij,t}$ Active power flow in circuit ij in time interval t [kW].

$P^g_{i,t}$	Active power generated at node i in interval t [kW].
$P^g_{i,t}$	Active power demanded by the PEV at node i in time interval t [kW].
$Q_{ij,t}$	Reactive power flow of the circuit ij in time interval t [kVAr].
$Q^g_{i,t}$	Reactive power generated at node i in time interval t [kVAr].
$V_{i,t}$	Voltage magnitude at node i in time interval t [V].
$x^v_{i,t}$	Binary variable associated with the PEV charging state at node i in time interval t.

List of Captions for Tables

Set of Tables

Table 1: PEV Charging scenarios

Cases	Priority	DG
A	✓	-
B	✓	✓
C	-	-
D	-	✓

.

Table 2: Comparative table of the the objective function in each PEV charging scenario.

Time limit		300 s			600 s			1200 s			4 Hours		
Case		Grasp	Tabu	Hybrid	Grasp	Tabu	Hybrid	Grasp	Tabu	Hybrid	Grasp	Tabu	Hybrid
47%	A	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67	-1540.67
	B	-1616.62	-1614.93	-1616.28	-1616.28	-1614.93	-1616.62	-1616.62	-1614.93	-1616.62	-1615.69	-1614.93	-1617.30
	C	515.12	515.47	514.85	514.90	515.17	514.59	515.23	514.62	514.59	515.02	514.62	514.59
	D	449.12	450.69	448.90	448.70	450.69	448.53	449.23	450.69	448.47	449.47	450.69	448.30
63%	A	-2856.42	-2856.76	-2856.92	-2857.30	-2856.76	-2857.34	-2857.33	-2856.76	-2857.34	-2857.34	-2856.76	-2857.34
	B	-2926.39	-2926.43	-2927.51	-2927.05	-2926.43	-2927.61	-2927.38	-2926.43	-2927.72	-2927.05	-2926.43	-2927.72
	C	557.82	2264.29	557.41	556.99	557.93	556.87	557.04	556.95	556.71	557.05	556.95	556.58
	D	492.35	493.73	491.98	492.06	493.73	491.78	492.10	493.17	491.35	491.93	491.62	491.28

Table 3: Percentage deviation of the objective function in each PEV charging scenario.

Time limit		300 s			600 s			1200 s		
Case		Grasp	Tabu	Hybrid	Grasp	Tabu	Hybrid	Grasp	Tabu	Hybrid
47%	A	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	B	0.00	0.10	0.02	0.02	0.10	0.00	0.00	0.10	0.00
	C	0.10	0.17	0.05	0.06	0.11	0.00	0.12	0.01	0.00
	D	0.15	0.50	0.10	0.05	0.50	0.01	0.17	0.50	0.00
63%	A	0.03	0.02	0.01	0.00	0.02	0.00	0.00	0.02	0.00
	B	0.05	0.04	0.01	0.02	0.04	0.00	0.01	0.04	0.00
	C	0.20	306.73	0.13	0.05	0.22	0.03	0.06	0.04	0.00
	D	0.20	0.48	0.13	0.15	0.48	0.09	0.15	0.37	0.00
Average Deviation		0.09	38.51	0.06	0.04	0.19	0.02	0.06	0.14	0.00

Table 4: Total operational cost of the 449-node system using HOA methodology.

47% - PEV Charging						
Cost ($)	Uncoordinated Charging	A	B	Uncoordinated Charging	C	D
ω	19.94	16.61	14.66	13.80	13.59	12.04
δ	28334.13	0.00	0.00	81459.67	0.00	0
φ	0.00	0.00	0.00	0.00	0.00	0
γ	-2793.47	-2120.38	-2129.18	0.00	0.00	0
β	575.71	563.11	497.22	499.33	501.00	436.26
ψ	0.00	0.00	0.00	0.00	0.00	0
Total cost	26136.30	-1540.67	-1617.30	81972.79	514.59	448.30
63% - PEV Charging						
Cost ($)	Uncoordinated Charging	A	B	Uncoordinated Charging	C	D
ω	22.97	19.32	16.60	15.93	15.43	13.94
δ	687861.37	0.00	0.00	320947.34	0.00	0.00
φ	0.00	0.00	0.00	0.00	0.00	0.00
γ	-4190.21	-3515.10	-3515.07	0.00	0.00	0.00
β	651.13	638.45	570.76	536.55	541.15	477.34
ψ	0.00	0.00	0.00	0.00	0.00	0.00
Total cost	684345.26	-2857.34	-2927.72	321499.82	556.58	491.28

List of Captions for Illustrations

Set of Illustrations

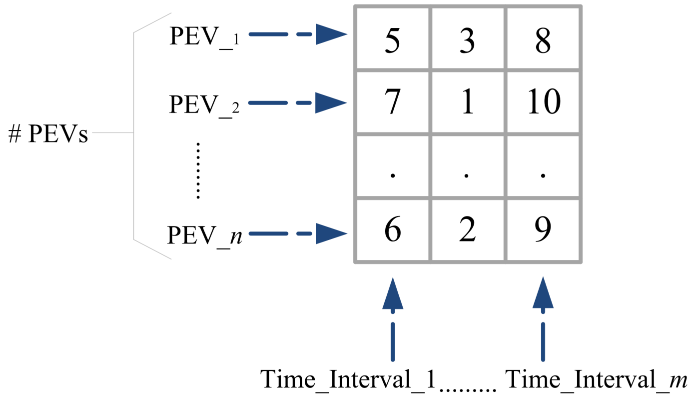


Figure 1: Example of the proposed codification.

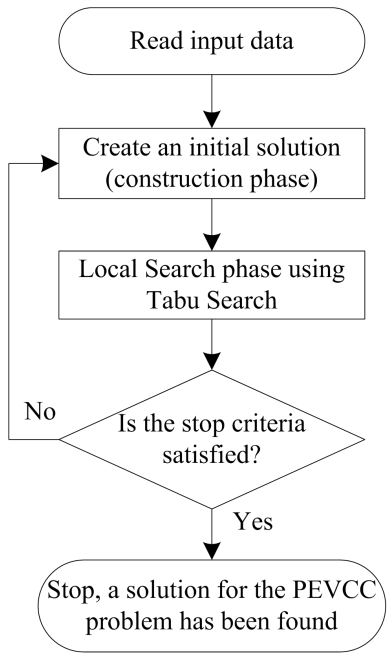


Figure 2: Flowchart of the proposed hybrid optimization algorithm.

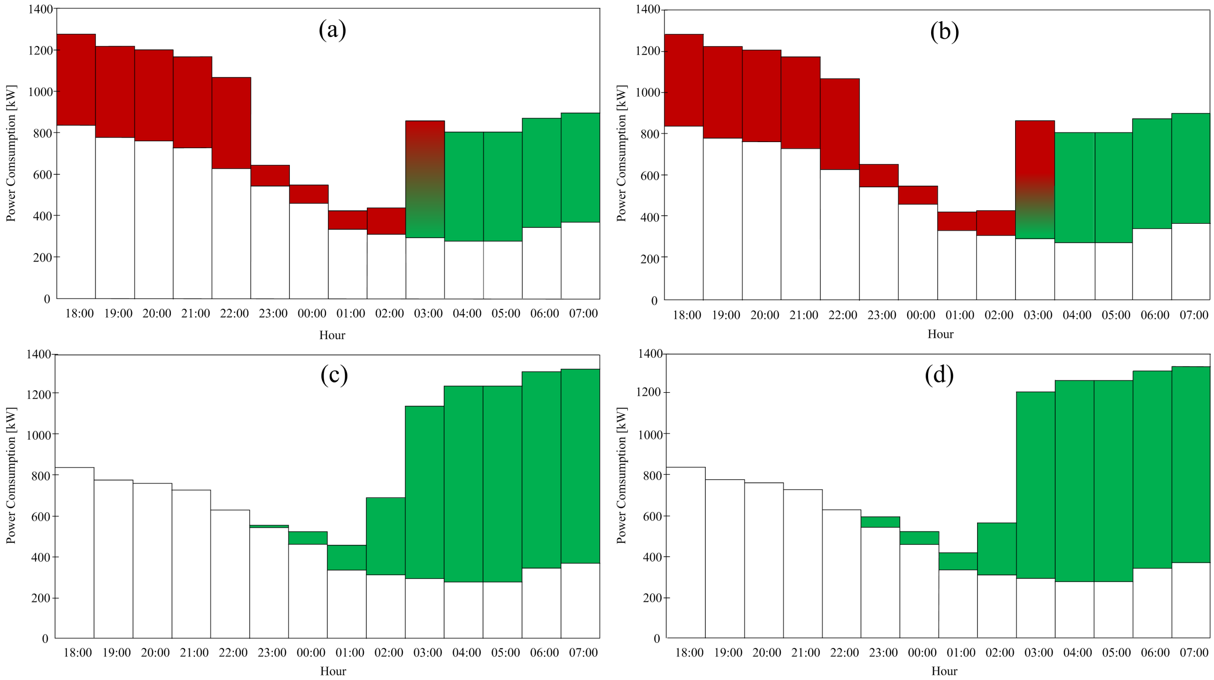


Figure 3: Power Consumption found by the HOA for the tests considering 47% PEV penetration: (a) Case A. (b) Case B. (c) Case C. (d) Case D.

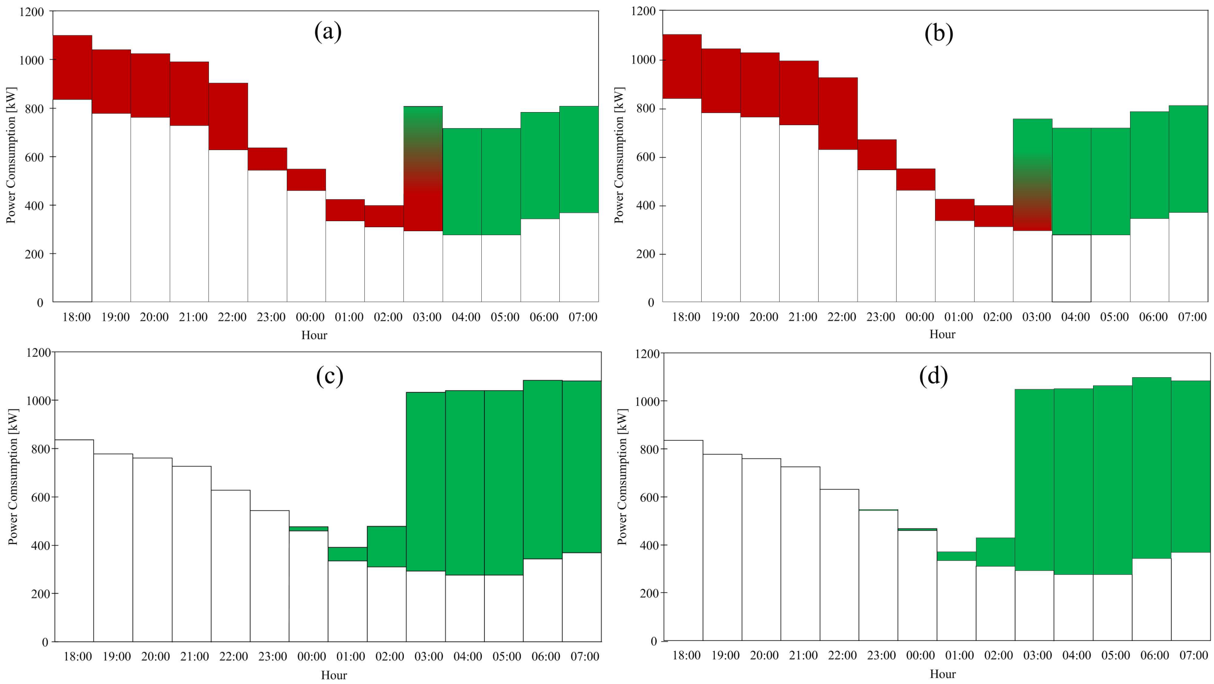


Figure 4: Power Consumption found by the HOA for the tests considering 63% PEV penetration (a) Case A. (b) Case B. (c) Case C. (d) Case D.

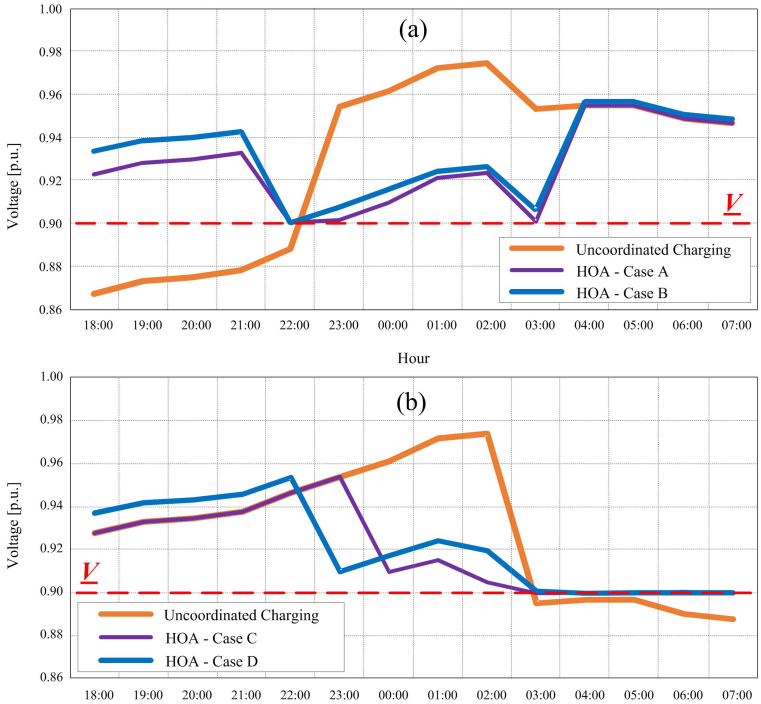


Figure 5: Minimum voltage for the cases with 47% PEV penetration. (a) Case A and B. (b) Case C and D.

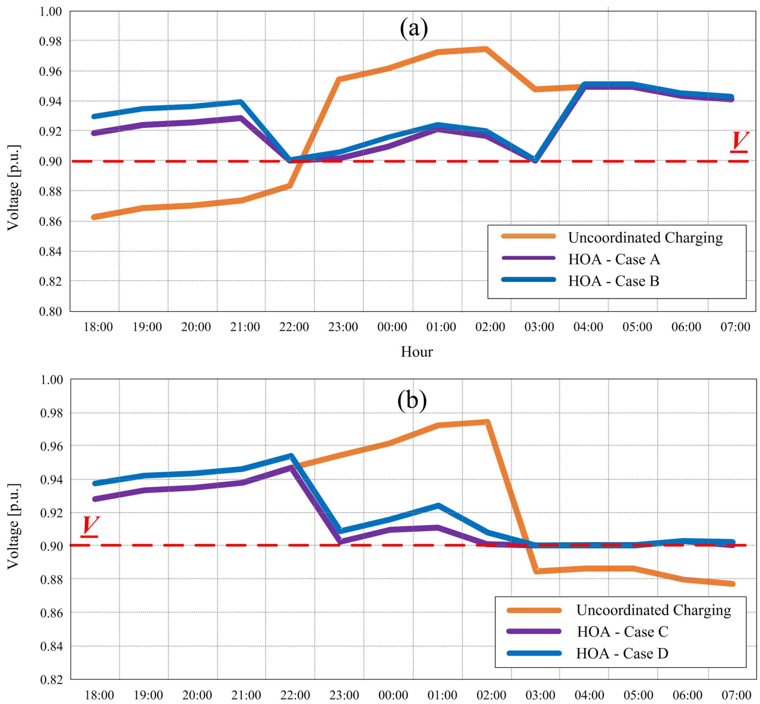


Figure 6: Minimum voltage for the system with 63% PEV penetration. (a) Case A and B. (b) Case C and D.

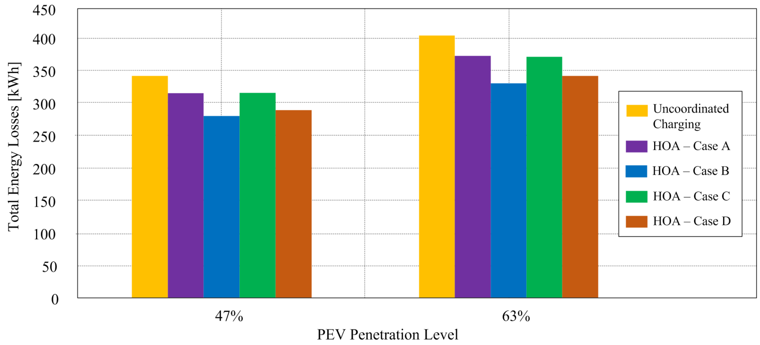


Figure 7: Total energy losses for the system.

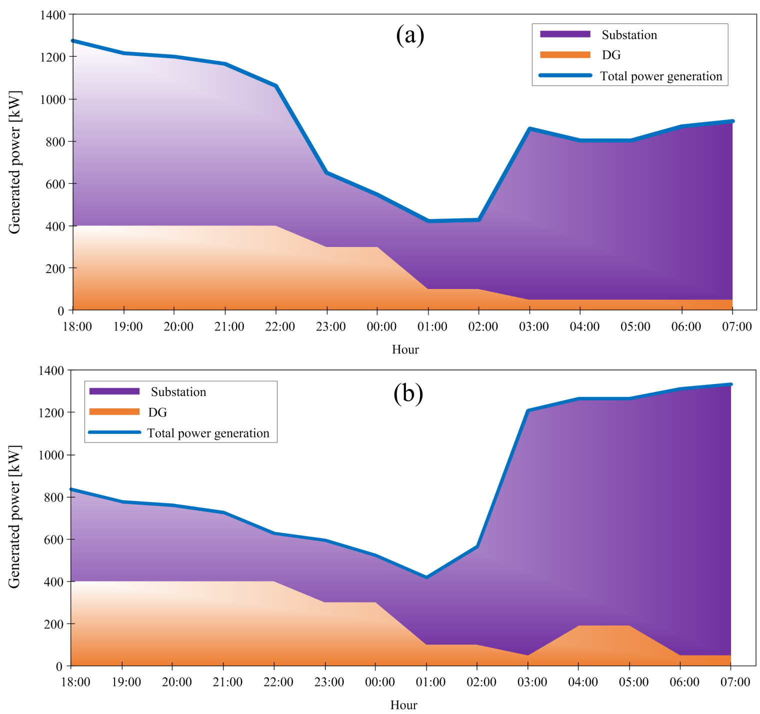


Figure 8: Generated power with 63% PEV penetration. (a) Case B (b) Case D.

E1. V2G Enabled EVs Providing Frequency Containment Reserves: Field Results

Nataly Bañol Arias
Electrical Engineering Department
UNESP – Sao Paulo State University
Ilha Solteira, São Paulo, Brasil
natycanta@aluno.feis.unesp.br

Seyedmostafa Hashemi, Peter Bach Andersen, Chresten Træholt
Center for Electric Power and Energy
Technical University of Denmark
Kongens, Lygnby, Denmark
{shtog, pba, ctr}@elektro.dtu.dk

Rubén Romero
Electrical Engineering Department
UNESP – Sao Paulo State University
Ilha Solteira, São Paulo, Brasil
ruben@dee.feis.unesp.br

***Abstract*—Frequency regulation is procured by transmission system operators (TSOs) to ensure stable and reliable operation of power systems. In the Nordic energy region, frequency-controlled normal operation reserve (FNR) is one of the services that require fast-response. Electric vehicles (EVs) with vehicle to grid (V2G) capability may be considered an FNR provider in a future renewable-based power system. This paper presents results from the first commercial V2G hub in the Nordic area using the EV fleet of Frederiksberg Forsyning. The results are achieved by participating in the Danish frequency regulation market, and provide an analysis of the EV fleet operational data. Additionally, an analysis on practical issues that may result from realistic implementation of frequency regulation, such as delays, measurement errors and physical equipment constraints is given. These issues must be taken into account when developing new strategies for providing frequency services with EVs in a future scenario. Results show that a set of EVs operating in aggregated mode is able to support the grid while satisfying the primary goal of the EV fleet, i.e. transportation of fleet customers.**

Keywords—Electric vehicles, EV fleet, Frequency regulation, Services, Practical issues.

I. INTRODUCTION

The stability and reliability of power systems can be jeopardized by increasing penetration of distributed energy resources due to the intermittent nature of their output power [1]. Transmission system operators (TSOs), who are responsible for the grid stability and security, maintain the balance between the electricity consumption and production by procuring ancillary services such as frequency and voltage regulation. Frequency regulation is one of the most common services procured by TSOs to ensure stable and reliable operation of power systems. The service can be provided by generation and/or by demand. A prominent and new option are pooled EVs due to the manageable nature of their loads, availability, bidirectional power capacity and quick response time [2]. Considering the entrance barrier in terms of power EVs should operate in an aggregated mode in order to ensure a sufficient capacity for participating in the frequency markets. Realistic implementations of frequency regulation using EV fleets in the North American market have been presented in [3]–[5]. In [3], the authors present an overview of a vehicle-to-grid (V2G) demonstration project, in which a real EV fleet provides frequency regulation in the California Independent System Operator (CAISO) market. A centralized method based on a mixed-integer linear programming model is developed to optimize the EV charging and the bid capacity while minimizing the operation cost and maximizing the profit of the aggregator for providing frequency regulation. In [4], a comparison between a centralized and decentralized method in terms of the bid capacity and the computational scalability is carried out based on simulations while in [5], the authors describe an implemented and deployed multi-agent system. In [6] a model is proposed to forecast the availability of an EV fleet for providing frequency regulation in the PJM market. The model is developed based on parameters such as route locations and the state of charge of the EVs. Comparing with [4] and [5], the work in [6] does not address a realistic implementation of frequency regulation using an EV fleet.

In European countries, frequency regulation using EV fleets have been studied in [7] and [8]. The authors in [7] develop an economic evaluation for an EV fleet participating in the French frequency regulation market, exploring regulation strategies for both unidirectional and bidirectional (V2G) power exchanges. Meanwhile, in [8] an analysis of frequency regulation services via V2G within a micro-grid environment is carried out in Macedonia. The results of the aforementioned works are based on simulations. Moreover, an analysis in [9] is focused on user behavior and EV energy consumption of a real EV fleet operation. Although a large amount of useful data regarding trips and state of charge of the EVs is provided in this work, the implementation of frequency regulation is not considered within the analysis.

In this paper, we focus on a real demonstration of frequency-controlled normal operation reserve (FNR) in Denmark provided by an EV fleet through the Parker project. This is the first project carrying out a demonstration of the participation of an EV fleet in the Nordic area. For this demonstration Nissan EVs, electric vehicle supply equipment's (EVSEs), commonly known as chargers and an aggregation software were used. Thus, the EVs provide regulation power to the grid through the EVSEs, which, at the same time are equipped with telecommunication between the EVs and the aggregator. The aggregator is responsible for bidding into the market and facilitates the communication between the EV owners and the TSO. It also controls the charging or discharging power of each EV using the aggregation software. This paper covers: 1) An assessment of the operation of an EV fleet that participates in the Danish frequency regulation market, which demonstrates that EVs are able to support the grid; 2) analysis of the practical issues that may result from the provision of frequency regulation using EV fleets in realistic environment.

The remaining part of this paper is organized as follows. In Section II, the Danish frequency regulation market along with the regulation services using an EV fleet are described. Section III presents and analyzes the EV fleet operation providing FNR based on one-week real data. Finally, the conclusions and the future work are presented in Section IV.

II. Frequency Normal Operation Reserve Provision by Frederiksberg Forsyning EV Fleet

A. Danish Frequency Regulation Market

Europe is split into five synchronous areas defined by the European Network of Transmission System Operators (ENTSO-E) with a nominal frequency of 50 Hz, without being synchronized with each other. Denmark is split into two synchronous areas: Jutland and Funen belong to Regional Group (RG) continental Europe and Zealand belongs to RG Nordic. These areas are termed Western Denmark or DK1 and Eastern Denmark or DK2, respectively. Available frequency reserves in DK1 and DK2 are presented in Table I [10]. Frequency-controlled reserves are procured to ensure balance between consumption and generation in real-time. The aim is to automatically stabilize the frequency at 50 Hz and minimize frequency deviations. The EV fleet subjected to this analysis is providing Frequency-controlled normal operation reserve (FNR) services to Energinet, which is the TSO in Denmark.

FNR is an automatic response provided by production or consumption units. It is a bidirectional frequency control activated for both under and over frequencies. According to the Danish market rules regarding FNR only symmetrical bids are allowed, which means that up and down regulations reserves should be offered together [10]. In the Danish frequency regulation market, the TSOs in the Nordic Synchronous area are responsible for the supply of FNR reserves. The combined requirement in the ENTSO-E RG Nordic is 600 MW and each TSO contributes separately to the total requirement. In this case, Energinet is responsible for the supply based on the production in Eastern Denmark. When the frequency deviation is up to +/-100 mHz compared with the reference (50Hz), FNR must be activated according to the linear function depicted in Fig. 1. The service must be fully activated within 150 seconds while continuously supplying power.

FNR is procured one or two days ahead of the day of operation. The suppliers can submit hourly bids, or in time blocks, under special conditions. All bids must be submitted via the self-service portal of Energinet. Bids submitted to the auction two days before must be submitted no later than 15:00h, and those submitted to the auction one day before must be submitted no later than 18:00h the day before. The volume and the hour-by-hour price must be defined in the bidding process in MWs and DKK/MW or EUR/MW, respectively. Moreover, the minimum bid must be 0.3MW. All bids are sorted and accepted according to price, until the total requirement is covered. The service is compensated based on an availability payment and pay-as-bid, and in case of activation, it is compensated using the regulating power prices for upward and downward regulation. Moreover, the players should be able to provide any documentation from the SCADA system in case that Energinet decides to check the service. The checking process is carried out by sampling or, when notable frequency deviations are observed.

To participate in the frequency market EVs act as production or consumption units. It means that they would charge and/or discharge their batteries depending on the frequency signal using the battery as a storage device. Thus, when upward regulation is required the EVSE should discharge the battery, while in downward regulation the EVSE should charge the battery, as shown in Fig. 2.

TABLE I. Reserve available in DK1 & DK2

	DK1	DK2
	Primary frequency reserve (PFR)	Frequency-controlled disturbance reserve (FDR)
Service	Secondary reserve, aFRR	Frequency-controlled normal operation reserve (FNR)
	Manual reserves, mFRR	Secondary reserve, aFRR
		Manual reserves, mFRR

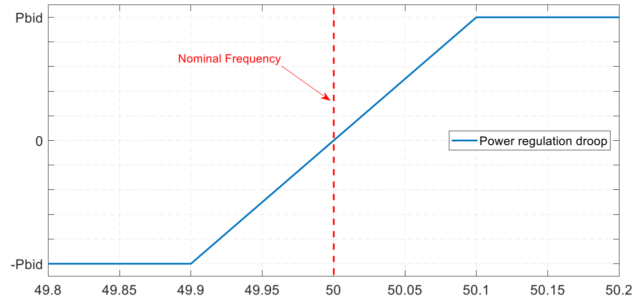


Fig. 1. Droop control for FNR service.

B. Frederiksberg Forsyning EV Fleet composition

The EV fleet of Frederiksberg Forsyning is providing FNR services to Energinet, the Danish TSO, through the aggregator. The EV fleet is part of a public utility company (Frederiksberg Forsyning) which is dedicated to provide maintenance services related to domestic gas, tap water, district heating and sewage in the greater Copenhagen. The EV fleet is composed of 10 Nissan eNV200 electric vans with battery capacity each of 24 kWh.

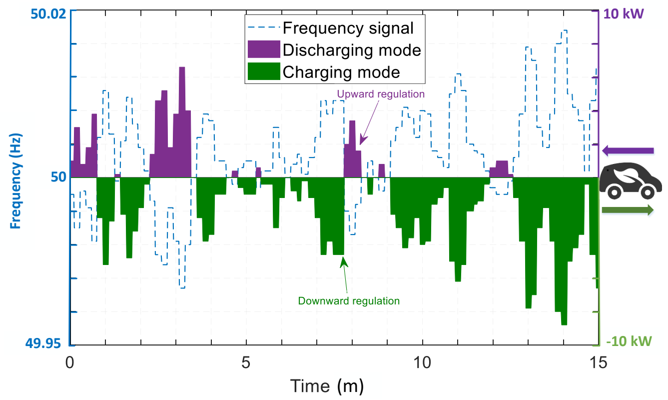


Fig. 2 FNR service provided by EVs..

There are 10 ENEL V2G chargers with maximum and minimum power rating of +/- 10 kW, allowing for simultaneous charging of all EVs. Fig. 3 depicts some of the cars and chargers in the utility company [11].

A. Aggregator

The role of the aggregator, as the name suggests, is aggregating a group of EVs and presenting them as a single unit to the system operator, facilitating the communication between the EV owners and the TSO [5]. The aggregator has the responsibility of bidding into the market as well as accomplishes the bid commitments. After the submission and acceptance of the bids, the aggregator must schedule the EV fleet operation following the frequency signal. The EVs should be scheduled hour-by-hour according to the regulation power decided in the bid process. The frequency signal is measured with one-second resolution and it should be followed by the EVs considering a preferred operating point (POP) [5]. The POP is a mechanism used to ensure a suitable EV's state of charge (SOC) to be able to provide regulation services at any time. Thus, the POP mechanism avoids the EV to be fully charged or fully discharged along the regulation period.

B. Communication process between the parties

A communication structure between the chargers, the EVs, the aggregator and the TSO is required. During the regulation period, the TSO sends signals to the aggregator, requesting the contracted frequency services. The aggregator must supply the requirements by controlling the charging or discharging power of each EV at any time. Therefore, the aggregator calculates the total power required based on the frequency signal, and afterward, divides it between all the EVs available for providing services at that specific time, according to an internal algorithm. This procedure determines the control actions for each EV. For this purpose, the chargers are equipped with devices that allow the communication between the EVs and the aggregator. These devices have implemented a mechanism called "Grid Integrated Vehicle (GIV)" which comprises a set of algorithms properly developed by the aggregator [4], used to control the power of the EVs.

III. Analysis of the Field Results

The analysis of the EV fleet operation has been carried out based on data from one complete week, from Friday 9th to Saturday 17th of September 2017 with one-second resolution. The data contains information related to the SOC of the EVs,

Fig, 3 EV fleet in the headquarter of Frederiksberg Forsyning [11].

power bid, power requested, and power provided. A detailed analysis of these parameters will be presented in this Section. For simplicity and better comprehension, some of the analysis will carried out using shorter periods, for instance, one day, one hour, or minutes.

A. Communication process between the parties

- The frequency regulation period considered for the analysis starts from 16:00h to 06:00h of the next day.
- The capacity of the EV batteries is 24 kWh. However, considering the customer preference and the battery life span, the working capacity for FNR is decreased.
- The power rated of each charger is 10 kW. However, the maximum and minimum power rated used for providing FNR is +/- 9.25 kW.

B. Analysis for one individual car during the complete week

1) SOC behaviour: Fig. 4a. shows the SOC of one specific car during the complete week. As can be seen, the SOC of the EV between September 10th and 11th does not have any interruption because this period corresponds to one weekend day, in which the car is available to provide service at any time. On the contrary, during the other days, there are interruption periods corresponding to the workday where the car is out driving. Additionally, note from Fig. 4a. that the initial SOC of the EV is different at the beginning of each regulation period. It is because the initial SOC of the EV highly depends on the user behavior. In this EV fleet, the EVs are used mainly for maintenance and service tasks. Then, the initial SOC depends on the kilometers driven during the work time, i.e., between 08:00h and 16:00h. Similarly, the final SOC at the end of the regulation period (06:00h) is different each day. This value depends on the exchanged energy during the regulation period. It is important to mention that the EV should be fully charge before the starting time of the workday. In this way, the period between 06:00h and 07:59h is used to bring the SOC of the EV to a suitable level before the departure time. The daily SOC behaviour provides useful information for the aggregator, since it defines the daily available energy from each car to provide regulation services. Based on this information, the aggregator

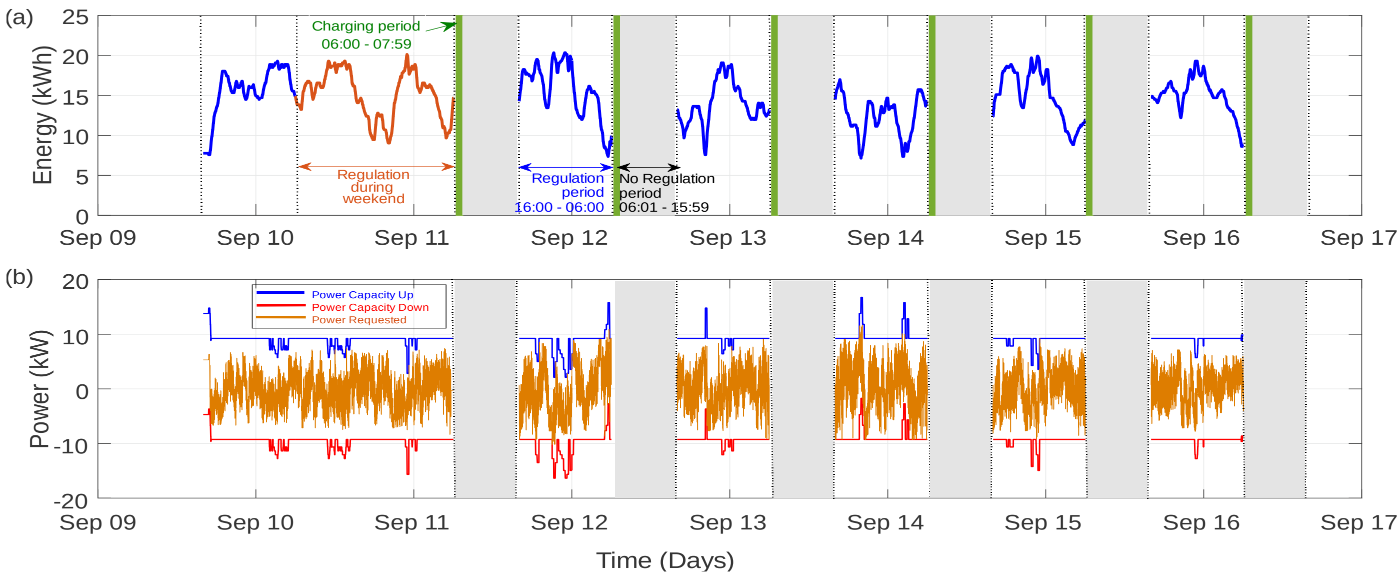


Fig. 4 Analysis of one car during the complete week. a) SOC behaviour. b) Power bid capacity and power requested.

can calculate the daily estimated bid capacity of each EV in order to optimize its participation in the market.

2) Availability of the car: The fact that the EV is not always available to provide services can be seen in Fig. 4a. Note that during the weekend the EV is only used to provide regulation services, i.e. it is parked (and plugged-in) the whole day. In contrast, during weekdays there is a period in which the EV does not provide services. It corresponds to the work hours (between 08:00h and 16:00h), in which the EV is used for customer services. Since the departure and the arrival time of each EV highly depend on the user behaviour, further statistical analysis focused on weekdays can be carried out, in order to increase the availability of the cars for services provision during this period, and in an attempt to improve the aggregator profit.

3) Up and down regulation: Fig.4b. shows that the power bid capacity for regulation up and regulation down is always symmetric, which is one of the requirements for providing FNR in the Danish market regulation. It can be seen that the power requested is always mantained between the limits of the power bid capacity.

C. Analysis for one individual car during one day

For this case, data from the regulation period during one weekday (between Tuesday 12th and Wednesday 13th of September 2017) is considered.

1) Power requested, power provided and SOC: From Fig.5 it is possible to observe that the power requested and the power provided follow the same pattern, mantaining within the allowed limits of the charger, (i.e., around +/-10 kW). A similar behavior can be observed for the EV SOC, which is mantained between the maximum and minimum energy limits previously defined. Furthermore, Fig. 5 shows that the SOC of the EV changes according to the power provided during the regulation period, as expected.

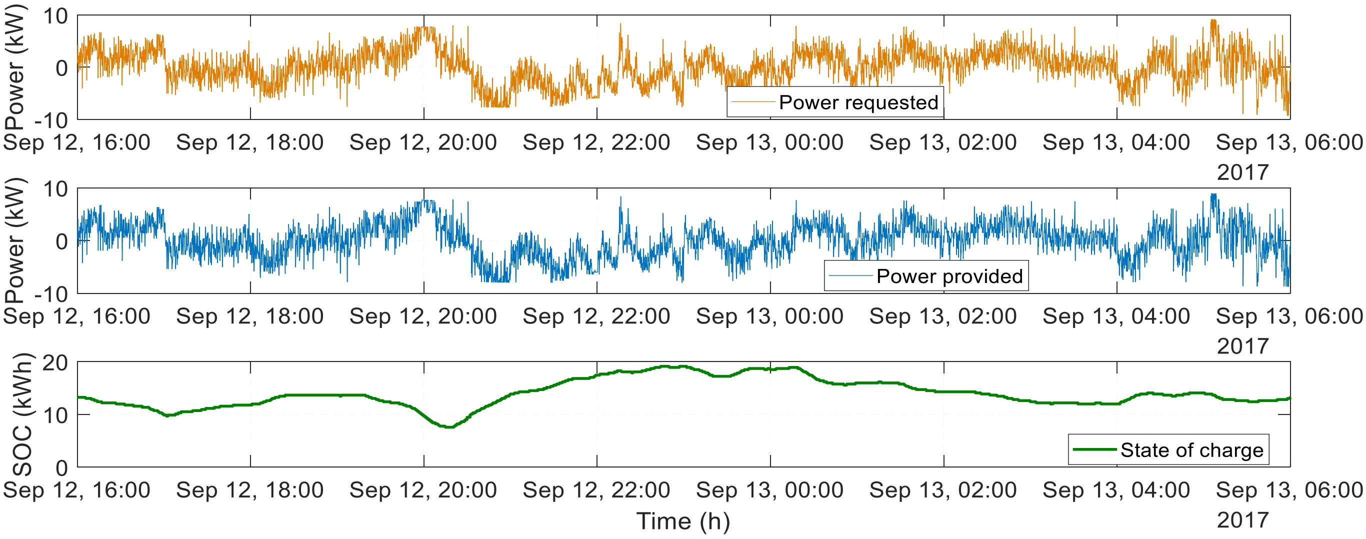
2) Difference between power requested and power provided: Fig. 5 shows that the power requested and power provided follow the same pattern. However, there are some small differences between them. Fig. 6 shows these parameters in detail, based on one second resolution data and for five minutes. It can be seen that the provided power curve slightly differs with the requested power curve in terms of response time and power. These differences may be as a result of delays in EVSE response, physical and technical constraints of the equipment, such as the current steps of the charger, or even by measument errors. It can be seen from Fig. 6 that the time delay is less than 10 seconds, meaning that a very fast response is provided compared to the FNR regulation requirements. These practical limitations should be considered whitin strategies developed to provide frequency regulation, in an attemp to avoid fines implied by failur to provide contracted service, and to improve the aggregator profit.

3) Total energy exchanged: Fig. 7 shows the total energy exchanged (charged and discharged) hour by hour. As can be seen, the amount of energy charged or discharged differs hour by hour. It highly depends on the frequency signal and less so on the SOC of the EV. Additionally, it can be seen that during some hours, e.g. 18:00h and 21:00h, the battery is only charged while in 16:00h and 02:00h is only discharged. This information is useful because the revenues are calculated partly based on the energy exchanged. Moreover, since the energy exchanced is directly related to the deph of discharge of the battery, this information can be used when developing strategies to estimate and optimize the life span of the battery.

D. Analysis of the EV fleet during weekend and weekdays.

For this case, measurements from the regulation period during one weekend day (between Friday 09th and Saturday 10th of September 2017) and for one weekday (between Tuesday 12th and Wednesday 13th of September 2017) are considered.

1) SOC behaviour: Fig. 8 depicts the SOC for all EVs. As can be seen the initial SOC for all cars and the SOC behavior along the entire regulation period are different for both days. However, the SOC of all EVs follows a similar behavior and at



Fig, 5 Power requested, power provided and SOC for one car.

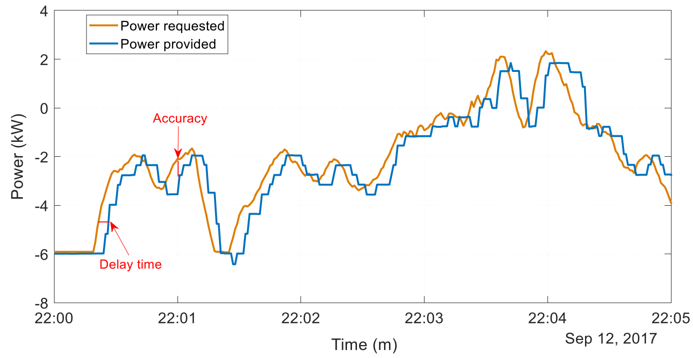


Fig. 6 Difference between power requested and power provided for one car.

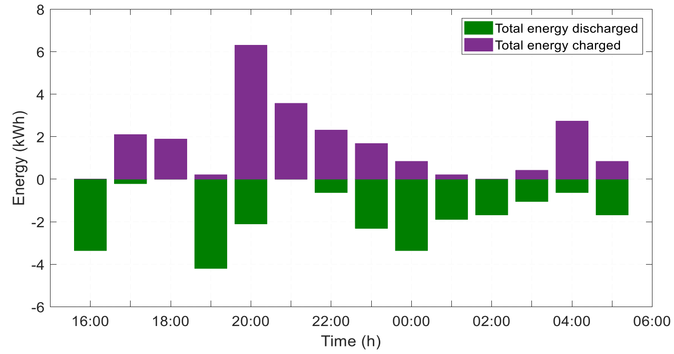


Fig. 7 Hourly energy exchanged for one car.

the end of the regulation period, it converges to a similar value. It occurs because the EVs should be prepared for transportation at the starting time of the workday. Moreover, the SOC behavior during the regulation period is similar because all the cars follow the same frequency signal, which defines the power required for each EV. However, it is not exactly the same because the SOC of each EV at the arrival time depends on the user behavior.

2) Charging-discharging limits: To ensure a higher life span of EV batteries and customer preference, maximum and minimum energy capacity limits should be maintained. Note in Fig. 8 that the SOC of all EVs is between 5 and 21 kWh.

3) Availability of the cars: As previously mentioned, during the weekend, the cars are used only to provide FNR, which gives the aggregator a higher chance of having all cars available for service provision. However, during weekdays many contingencies may occur decreasing the availability of the EVs. Note in Fig. 8 that the SOC of one EV during the weekday is equal to zero, which means that the car is not available to provide regulation services. This fact may affect the operation of other EVs in an attemt to maintain the services provision. Then, this kind of contingencies could be taken into account during the optimization of the bidding process in order to maximize the aggregator profit.

4) Power requested: Fig. 9 shows that the power requested for all EVs is the same most of the time, although there are some periods in which it slightly differs for certain cars. Note from Fig. 9 that at the beginning of the regulation period (16:00), some cars have different power requested. As time goes by, the power requested for all EVs converges to a same value until a decoupling occurs. After this event, a stabilization period is requiered untill all EVs reach the same power required again. The power requested and the POP of all EVs are depicted in Fig.10.

IV. CONCLUSION AND FUTURE WORK

Field results from the EV fleet of Frederiksberg Forsyning, the first commercial V2G hub in the Nordic area providing FNR services were highlighted and analyzed in this paper. Results showed that a pool of EVs operating in aggregated mode are able to in a comprehensive manner support the grid with fast frequency regulation, such as FNR. It was also observed that

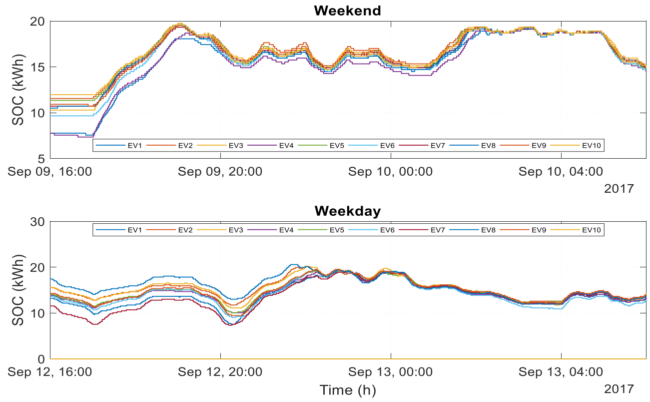


Fig. 8 SOC for each car of the EV fleet.

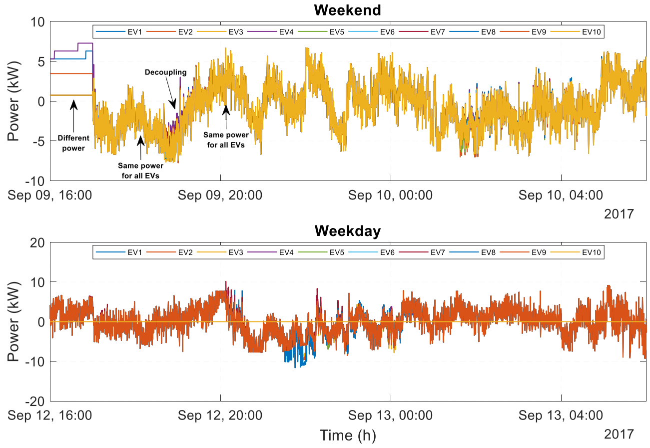


Fig. 9 Power requested for each car of the EV fleet.

the availability of the EVs plays an important role in the bidding process, especially during weekdays. Further analysis of the individual EV patterns could be carried out in order to increase the aggregated among of power used to participate in the market. Further analysis of the EV fleet operation during working hours could also be addressed.

Additionally, practical issues, such as communication delays, measurement errors and physical equipment constraints that result from real implementations of FNR, were identified. Considering these limitations within the bidding strategies could substantially improve the efficiency of the regulation service as well as the revenues of the aggregator. As future work, an optimized bidding strategy will be proposed, taking into account the availability of EVs during working hours, aiming at improving the aggregator profit.

Acknowledgment

The authors would like to thank NUVVE for the provision of data used in this research. This work is supported by the Danish research Parker project under ForskEL contract no. 2016-1-12410, http://parker-project.com.

Nataly Bañol Arias is supported by the Brazilian institution CAPES: PSDE (Programa de Doutorado Sanduíche no Exterior), process nr. 88881.135226/2016-01.

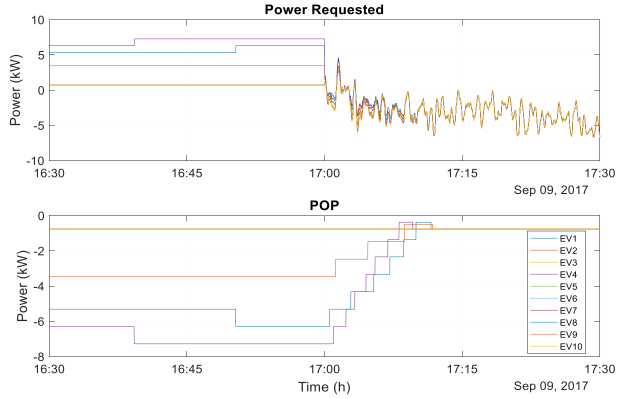


Fig. 10 Power requested for each car of the EV fleet.

References

[1] R. Bayindir, S. Demirbas, E. Irmak, U. Cetinkaya, A. Ova, and M. Yesil, "Effects of renewable energy sources on the power system," in 2016 IEEE International Power Electronics and Motion Control Conference (PEMC), 2016, pp. 388–393.

[2] E. Romero-Cadaval, F. Barrero-González, E. González-Romera, and M.-I. Milanés-Montero, "Using plug-in electric vehicles to implement ancillary services in smart distribution grids," in Plug In Electric Vehicles in Smart Grids: Integration Techniques, S. Rajakaruna, F. Shahnia, and A. Ghosh, Eds. Singapore: Springer Singapore, 2015, pp. 309–349.

[3] N. DeForest, J. S. MacDonald, and D. R. Black, "Day ahead optimization of an electric vehicle fleet providing ancillary services in the Los Angeles Air Force Base vehicle-to-grid demonstration," Appl. Energy, 2017.

[4] S. Vandael, T. Holvoet, G. Deconinck, S. Kamboj, and W. Kempton, "A comparison of two V2G mechanisms for providing ancillary services at the University of Delaware," 2013 IEEE Int. Conf. Smart Grid Commun., no. October, pp. 211–216, 2013.

[5] S. Kamboj, W. Kempton, and K. S. Decker, "Deploying Power Grid-Integrated Electric Vehicles as a Multi-Agent System," Inf. Sci. (Ny)., no. Aamas, pp. 13–20, 2011.

[6] J. D. Fitzsimmons et al., "Simulation of an electric vehicle fleet to forecast availability of grid balancing resources," 2016 IEEE Syst. Inf. Eng. Des. Symp. SIEDS 2016, pp. 205–210, 2016.

[7] P. Codani, M. Petit, and Y. Perez, "Participation of an electric vehicle fleet to primary frequency control in France To cite this version : frequency control in France," Int. J. Electr. Hybrid Veh., vol. 7, no. 3, pp. 233–249, 2015.

[8] S. Cundeva and A. Dimovski, "Vehicle-to-grid system used to regulate the frequency of a microgrid," 17th IEEE Int. Conf. Smart Technol. EUROCON 2017 - Conf. Proc., no. July, pp. 456–460, 2017.

[9] C. De Cauwer, M. Maarten, S. Heyvaert, T. Coosemans, and J. Van Mierlo, "Electric vehicle use and energy consumption based on real- world electric vehicle fleet trip and charge data and its impact on existing EV research models," EVS28 Int. Electr. Veh. Symp. Exhib., pp. 1–11, 2015.

[10]Energinet.dk., "Ancillary services to be delivered in denmark. Tender conditions," 2017.

[11]"DANMARK, NISSAN NEWSROOM. Nissan, Enel and Nuvve operate world's first fully commercial vehicle-to-grid hub in Denmark," 2016. [Online]. Available: https://newsroom.nissan-europe.com/dk/da-dk/media/pressreleases/149191. [Accessed: 19-Nov-2017].

E2. Distribution System Services Provided by Electric Vehicles: Recent Status, Challenges, and Future Prospects

Nataly Bañol Arias, *Member, IEEE*, Seyedmostafa Hashemi, *Member, IEEE*, Peter B. Andersen, *Member, IEEE*, Chresten Træholt, *Member, IEEE*, and Rubén Romero, *Senior Member, IEEE*

***Abstract*-Trend-setting countries have promoted or even employed an increased number of electric vehicles (EVs) and other distributed energy resources (DERs) in their power systems. This development has triggered new and increasing challenges in the distribution system planning and operation, whereby distribution systems must adapt to the increased share of DERs. However, EVs may also offer new opportunities and can be used to support the grid by providing several local and global power- and energy-based services. This paper presents a review and classification of the services potentially available from EVs for distribution systems, referred to as EV distribution system services (EV-DSS). A detailed description of recent services and approaches is given, and an assessment of the maturity of EV-DSS is provided. Moreover, challenges and prospects for future research are identified, considering key topics, such as the design of the market framework, economic assessment, battery degradation, and the impacts of the transmission system operator service provision by EVs on distribution networks. Thus, this work offers a tool for stakeholders concerning services available from EVs and provides a broad literature framework that can be used as a base for further investigations. It is aligned with the current requirements to move toward realistic implementations of EV-DSS.**

***Keywords* - Distribution Systems, Distribution System Services, Electric Vehicles, Renewable Energy Sources, Services Classification, Smart Grids.**

I. Introduction

RECENTLY, the concept of ancillary services for distribution networks has become a new paradigm in conjunction with the new roles assumed by distribution system operators (DSOs) in modern energy systems. With the advent of smart grids an increased amount number of distributed energy resources (DERs) in power systems has triggered new and increasing challenges in distribution system planning and operation. Hence, distribution systems are required to assume new responsibilities and procure additional services to maintain high-quality services for end users.

These services can potentially be provided by batteries, including stationary batteries, and electric vehicles (EVs). An advantage of using stationary batteries is their permanent availability, which makes it possible to provide reliable services. However, the initial investment in stationary batteries is relatively high. EVs have the advantage in that they are purchased for a primary purpose, which is transportation, and that the service provision has second priority, but can offer alternative income for EV owners when the car is not being used for transportation.

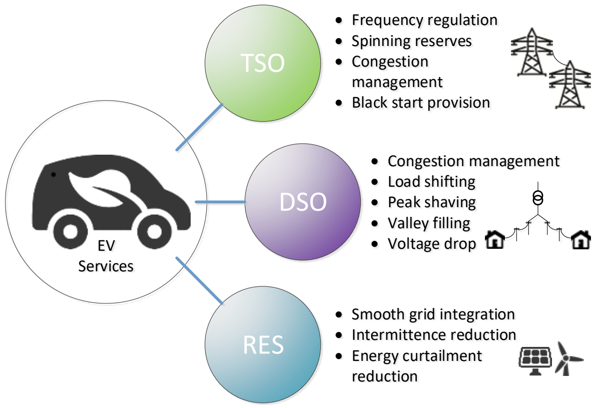


Fig. 1. EV services provided for different parties in power systems.

Global EV penetration is increasing progressively. The increase is motivated by social, economic, and environmental factors, such as the support for transportation electrification from government policies, lower running costs, and the idea that EVs may address climate change and local air quality by reducing greenhouse gas emissions [1]. Consequently, it is anticipated that EVs will be integrated into the power systems in the future. Many studies have highlighted operational problems caused by EV integration into distribution systems. Increases in peak load, energy losses, overload of grid components, voltage drops, and, consequently, decreases in service quality are some of the adverse effects of a high EV penetration [2]–[4]. However, several works have been proposed in the literature to deal with these problems by using charging control algorithms and smart strategies in which EV charging is properly managed to decrease the challenges associated with EV integration [5]–[7]. EVs may also play an important role in the integration of renewable energy sources

Manuscript submitted April 04, 2018. This work was supported by the Danish research Parker project under ForskEL contract no. 2016-1-12410 and by the Brazilian institution CAPES: PSDE, process no. 88881.135226/2016-01.

N. Bañol Arias and R. Romero are with the Electrical Engineering Department, UNESP – São Paulo State University, Ilha Solteira, CEP 15385-000, Brazil. (e-mail: natycanta@aluno.feis.unesp.br; ruben@dee.feis.unesp.br).

S. Hashemi, C. Træholt, and P. B. Andersen are with the Center for Electric and Energy, Department of Electrical Engineering, Technical University of Denmark (DTU), Kgs. Lyngby 2800, Denmark. (e-mail: shtog@elektro.dtu.dk; crt@elektro.dtu.dk; pba@elektro.dtu.dk).

(RES) into distribution systems. Several studies have focused on the joint operation of EVs and RES facilitating smooth grid integration of intermittent renewable sources [8]–[10]. Although EVs are loads that have to be supplied by distribution systems, they may also offer new opportunities. Due to the manageable nature of their loads, they can be used to support the grid by providing several local and global power- and energy-based services. Fig. 1 illustrates some of the services that can be provided by EVs to different parties in the power system.

Most literature focuses on the services that EVs can provide for the transmission system operators (TSOs), usually called *ancillary services*. Frequency regulation, for instance, a service required by TSOs, has been widely addressed in the literature [11]–[16]. However, since the concept of services provided by EVs for DSOs is a new paradigm, most of the studies that have investigated distribution system services provided by EVs (EV-DSS) remain in theoretical applications.

EV-DSS are considered to be a set of flexible strategies that are provided to maintain an optimized and reliable operation of the local grid. In [17], the services that EVs can provide to DSOs, along with possible market structures, are discussed. In [18], a review on EV fleet management in smart grids is conducted. The authors develop a classification of different methods for the smart charging of EVs without focusing on EV-DSS. In [19], the feasibilities of certain services are evaluated for EVs in an aggregated mode, enabling DSOs to provide ancillary services for TSOs. In [20] and [21], the authors assess the framework, benefits, and challenges of vehicle-to-grid (V2G) technology and conduct a review of optimization techniques. [21] also includes a review of energy storage technologies deployed in EVs and the current regulations, standards, and issues within smart grids. Similarly, [22] and [23] review the EV technologies, their connectivity, impacts on the grid, benefits, and standards of EVs with RES in future smart grids. However, from the aforementioned works, some of the classifications are not clear about who receives more benefits from these services. Furthermore, there is no consistency in the name and definition of the EV services. By having a clear definition and classification of the services that EVs can provide at the distribution system level, it is possible to give EV-DSS a formal standing. Moreover, from the literature review, it is possible to identify that the requirements for a realistic implementation of EV-DSS have not been thoroughly investigated. We have identified that key topics, such as market framework design, economic assessment, battery degradation, the impact of TSO service provision on distribution networks, and emerging EV technologies and their impact in the distribution grid need further investigation to ensure an active and efficient participation of EVs in providing services for DSOs.

The primary goal of this paper is to identify the research gaps that need to be addressed to move toward a realistic implementation of EV-DSS. Aiming at completing the picture of potential EV-DSS, this paper contributes to the following. First, an up-to-date classification and description of the services that EVs can provide for distribution systems are presented as a first step to formally label EV-DSS. Second, a review of the recent literature is provided, including information regarding V2G technology; methodologies and solution techniques; and consideration of the uncertainties, software, solvers, and characteristics of the test systems used in each approach. Third, a framework is presented comparing the work that has been done in the academic research with a real-life application using a specific case of frequency regulation. Finally, a comprehensive discussion is provided regarding the challenges and prospects of the EV-DSS, including key topics such as market framework, economic assessment, battery degradation aspects, impacts of the TSO service provision by EVs on distribution networks, and the impact of EV emerging technologies on the distribution grid. The information gathered in the second part provides an overview of the traditional methods and allows us to identify weakness in the control strategies as a means to encourage exploring new strategies aligned with the current requirements in realistic implementations of EV-DSS. The goal of the comparison in the third part is to assess the implementability of EV-DSS, i.e., how far the EV-DSS are from being implemented, and the stackability of EV-DSS, i.e., how easily EV-DSS can be combined with frequency regulation services. This is an innovative means to encourage the development of local DSO markets and promote the active participation of EVs as a service provider for DSOs.

Findings concerning battery degradation and the impact of the service provision to TSOs in distribution networks are supported by preliminary results obtained from the real implementation of the frequency-controlled normal operation reserve (FNR) provision to the TSO in Denmark [24]. This real implementation demonstrates that EVs are able to support power systems with their fast response; therefore, it is worth exploring the EVs' capability to support distribution systems. Accordingly, this paper contributes by encouraging new investigations on different aspects that remain unclear in order to move toward realistic implementations of EV-DSS.

The paper is organized as follows: Section II presents an overview of traditional classifications of EV services in power systems, and the proposed classification of the services provided by EVs specifically for DSOs is described. Section III describes the contributions of the reviewed works and discusses the weaknesses and research requirements. In Section IV, an assessment of the maturity of EV-DSS in real applications is carried out. Finally, challenges and future research suggestions are given in Section V, followed by the conclusions provided in Section VI.

II. Overview of Traditional Classifications of EV Services in Power Systems

The concept of ancillary services appeared with the disaggregation of generation, transmission, and distribution systems, and it was mainly created for transmission systems, which are responsible for grid stability and security [25]. Ancillary services, along with the corresponding market framework, can vary among countries, due to the structural differences in their power systems [26], [27]. From the distribution system point of view, the concept of ancillary

TABLE I. DIFFERENT CLASSIFICATIONS OF SERVICES PROVIDED BY EVS FOUND IN THE LITERATURE.

Reference	Category	Service
[18]	Congestion prevention	Peak load reduction, power loss
	Voltage regulation	-
[19]	Medium voltage grid	Peak power shaving, voltage regulation
	Low voltage grid	Peak power shaving, voltage regulation
	High voltage grid	Loss minimization
		Energy transmission cost minimization
		Frequency regulation
		Balancing mechanism (tertiary frequency control)
[20]	Power grid regulation	Frequency regulation
	Spinning reserves	-
	Active power support	Peak load shaving, load leveling, power loss
	Reactive power compensation	Voltage regulation, power factor correction
[23]*	Load management	Load shifting
	Power quality	Voltage regulation, load and voltage imbalance reduction
	Power regulation	Frequency regulation, balancing power flow, absorb ramping power, stability
[30]	Frequency control	Regulation up and down, spinning and non-spinning reserve
	Voltage control	-
	System restoration	-
[31]	Frequency regulation/control	-
	Loading services	Congestion prevention, loss reduction
	Voltage service	Voltage magnitude regulation, imbalance reduction
[33]	-	Frequency and voltage regulation
		Transient stability improvement
		Peak shaving
		Valley filling
		Spinning reserve
		Power flow optimization
		Power quality improvement
[34]*	Spinning reserve	-
	Time shifting	
	Active power support	
	Reactive power compensation	
[35]**	Frequency regulation	-
	Reserve	Spinning/non-spinning
	Peak load leveling	-
	Backup supply service	-
[36]**	Frequency regulation	-
	Spinning reserve	-
	Supplemental Reserves	Non-spinning reserves
	Replacement Reserves	Contingency reserve

* It was not specified whether the classification is for TSOs or DSOs.
** Classification for TSOs.

services provided to the DSOs is a new paradigm that has been emerging in conjunction with the new roles assumed by DSOs within the smart grid context. It appears as a set of flexible services that can be provided to deal with the operational challenges (i.e., the challenges arising from the integration of EVs and RES into the grid). Because the concept of ancillary services is mostly related to the services provided for the transmission system, this paper will refer to services provided for the distribution systems as *distribution system services* (DSS). The use of DSS may help prevent or defer grid upgrade, but may also improve the operation of the grid through better management [28], [29].

Table I shows a summary of different classifications for the services provided by EVs in power systems, based on the literature. This table is constructed from papers in which a specific classification of EV services has been described. Each paper proposed a classification including different categories and services, which are named according to each author's preferences. Table I presents a traditional idea of grid services and shows how people usually classify grid services. In [20], the authors establish the frequency regulation service as part of the power grid regulation category. Peak load shaving, load leveling, and power loss services are considered in the category of active power support, whereas voltage regulation and power factor correction are services considered in the category of reactive power support. In [30], the authors consider up-down regulation and spinning and non-spinning reserve services in the frequency control category. The classification proposed in [31] includes congestion prevention and loss reduction in the category of loading services, while voltage magnitude regulation and imbalance reduction are considered in the voltage services category. Similarly, in [18], peak load reduction and power loss services are considered in the congestion prevention category. The authors in [19] classify peak power shaving and voltage regulation for both medium and low voltage networks. The authors also propose an ancillary service called balancing mechanism, which is also found in the literature as a tertiary reserve [32]. Meanwhile, the authors in [33] do not specify categories; instead, they mention services such as frequency and voltage regulation, transient stability improvement, peak shaving, valley filling, spinning reserve, power flow optimization, and power quality improvement.

Some classifications found in the literature do not specify if the services are proposed for providing support to the DSOs or to the TSOs, as presented in [23] and [34]. Some references clearly specify if the services are proposed for supporting the transmission system, as presented in [35] and [36]. Moreover, in most of the studies related to ancillary services, it is difficult

TABLE II. PROPOSED CLASSIFICATION OF THE EV-DSS.

Category	Services	Related works	Alternative names
Active power support	Congestion management	[58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68],	Congestion alleviation, congestion prevention,
	Loss minimization	[19], [64], [69], [70], [71], [72], [73], [74], [81], [84], [96], [107], [111]	Loss reduction
	Load shifting	[72], [75], [76], [77], [78], [79], [80], [111]	Load leveling, load shaping, load flattening
	Peak shaving - valley filling	[19], [67], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90]	Load shedding, load curtailment, peak clipping, load variance, load shifting
	Voltage control by active power	[9], [19], [58], [59], [63], [64], [65], [70], [71], [80], [81], [91], [92], [93], [94], [95], [96], [97], [110]	Voltage regulation, voltage deviation reduction
Reactive power support	Reactive power compensation	[84], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110]	
	Voltage control by reactive power	[10], [69], [84], [98], [101], [102], [103], [104], [105], [106], [107], [109], [110], [111]	Voltage regulation
Renewable energy sources integration support	EV+PV	[9], [10], [78], [96], [97], [107], [121], [122], [123], [124]	
	EV+Wind	[10], [109], [121]	

to identify who receives the most benefits: DSOs or TSOs.

Based on the classifications in Table I, one can notice that there is neither an agreement nor a clear classification of the EV services provided for DSOs. There is no consistency in the name and definition of the EV services. Frequency regulation, for instance, is a service mainly offered for the transmission system [35], [37]–[41]. Nonetheless, some works mention that this service could be required in the future for DSOs [18], [30]. In that case, the EV control for frequency regulation in microgrids could be also considered as a service for DSOs, since they have the potential to improve microgrid stability when operating in an isolated mode, as discussed in [42]–[45]. Most of the papers do not specify which kind of regulation is studied. Instead, the regulation services are mentioned in different ways, such as load regulation or load following. Non-spinning reserves are also found as supplemental reserves, while replacement reserves and contingency reserves refer to the same service.

Based on the previous findings of the works presented in Table I, it is possible to observe that a) Most of the studies that have investigated services provided by EVs are addressed to services mainly provided to TSOs and not at the distribution system level; b) The current classifications of EV services are not clear about which stakeholder receives the benefits of these services; c) There is no clarity among the names given to different services, which makes it difficult to provide a consistent EV-DSS portfolio. The definitions of the offered services vary from market to market, and the classification of services depends mainly on the particular requirements of each DSO and the regulations of each country. For this reason, we proposed our own classification of EV-DSS, as a first step to move toward the formalization of DSO products. Having a clear definition and classification of the services that EVs can provide at the distribution system level makes it possible to identify the current requirements for realistic implementations. In the following sections, the proposed classification of the services provided by EVs specifically for DSOs will be presented.

2.1 Proposed classification of distribution system services provided by EVs

Table II presents the proposed classification of EV-DSS in which the services are classified into three main categories: active power support, reactive power support, and RES integration support. This table includes a list of references from the specialized literature, in which each service has been addressed. It also includes a list of some alternative names found in the literature for each service.

Active power or real power is the main source of revenue for DSOs, and it has become an important issue for distribution systems. Usually, active power accomplishes the useful work, while reactive power supports voltage. However, if both active and reactive power are not efficiently controlled, operational/technical problems (e.g., overloading, overvoltage, undervoltage, and power loss increases) may occur. Therefore, active and reactive power should be efficiently controlled in order to maximize the earnings of DSOs while maintaining system reliability.

Congestion management, loss minimization, load shifting, peak shaving, valley filling, and voltage control are involved in the category of active power support services (frequency regulation service is not included in this category because it is typically a service required by TSOs). Most of the services included in the active power support category are part of a large concept known as *demand side management*. Demand side management is a methodology in which the demanded energy is modified through different methods and incentives. Thus, demand is redistributed and spread more uniformly during the planning horizon. Demand side management comprises several initiatives and methods [46]–[48], which are depicted in Fig. 2.

Note from Fig. 2 that demand response appears as an initiative of demand side management, which aims to induce lower electricity consumption by changing the normal consumption patterns of demand-side resources in response to changes in the price of electricity, or incentive payments [49]. Demand response can be accomplished by price signals (indirect load control) or predetermined contracts (direct load control) [50], applying methods such as load shifting. Peak shaving and valley filling are also among the methods used in demand side management. However, they can also be found in the literature as complements to the load shifting method, pursuing similar objectives, such as reducing peak demand, reducing energy cost, and avoiding violations of technical limits. For this reason, peak shaving and valley filling are connected to load shifting through the blue arrow in Fig. 2. Representations of peak shaving, valley filling, and load shifting are illustrated in Fig. 3 [51].

Reactive power compensation and voltage control or voltage

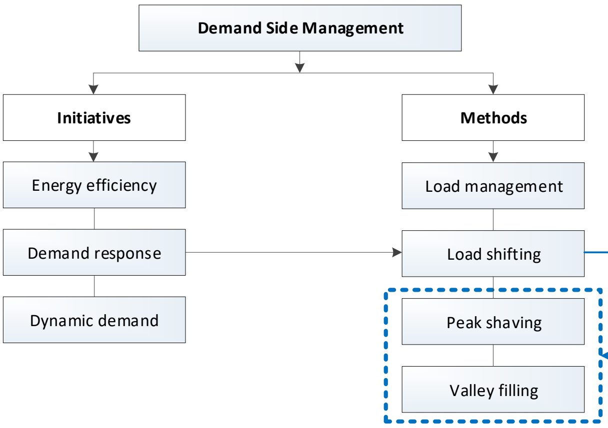


Fig. 2. Demand side management framework

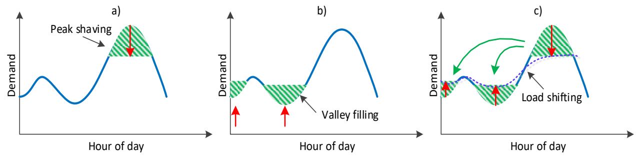


Fig. 3. Active power services a) Peak shaving b) Valley filling c) Load

regulation are involved in the category of reactive power support services. Note that voltage regulation support is a service included in both categories: active and reactive power support.

Regarding the services provided by EVs for supporting RES integration into the grid, the main service found in the literature is the coordination between the operation of EVs and RES, which is divided into two subcategories: the charging and/or discharging of EVs, along with photovoltaic energy (EV+PV) and charging, and/or the discharging of EVs along with wind energy (EV+Wind).

It is noticeable that a relationship between the services regarding active power support exists, as they pursue similar objectives. For instance, congestion management can be addressed by using load shifting in an indirect way. Peak shaving and load shifting are similar services. Load shifting is performed by moving the load from peak to valley times, achieving shaving and filling. However, in load shifting, the load is kept as part of the global demand, whereas in peak shaving, it is removed [52]. Some of the papers found in the literature address active power support services using different names. For instance, some studies address load shifting, load leveling, or load shaping, the last being the most generic term. Nonetheless, they may have different purposes. In energy storage applications, for instance, load shifting has the purpose of reducing peak demand, while load leveling has the same purpose, but for an economic operation [53]. Additionally, it was found that the term *load leveling* is used more frequently on the supply side, i.e., by electric utility companies, while peak shaving is used more frequently on the demand side, i.e., by electric utility customers [54]. The valley filling service can also be found as load variance or load shifting. Most of these services deal with peak events and prevent network overloading by reducing the peak power demand. Furthermore, they not only lower utility bills, but also reduce technical problems on the power grid. Therefore, each service is taken into account separately in order to present a clear classification of the EV-DSS.

The main contributions of each paper, along with the basic definitions and formulations of the services, are described in the next section. This material provides a guide for the reader regarding the approach to choose, depending on the EV-DSS under consideration.

III. Contribution of the Reviewed Works

In this section, the main contributions of the reviewed papers about EV-DSS are presented. Most of the reviewed papers are taken from recent literature. Table III shows a summary of the characteristics of the reviewed papers, including information related to the consideration of V2G technology, solution techniques applied to address the services, type of control (centralized or decentralized), and consideration of uncertainties within the methodology. Table III also includes information regarding the test system (e.g., number of buses, real or adapted systems, and one- or three-phase systems) and the type of software and solver used in the simulations. The list of papers is sorted chronologically. After classifying and describing the studies that have been done in the academic research in regard to EV-DSS, the weaknesses of the developed strategies and research requirements are identified and discussed.

3.1 Active power services

The EV demand could be considered a controllable load that can be managed for different purposes. It has been demonstrated that EVs are usually charged during the peak hours [55], when the price of electricity is high. Some services, such as load shifting, peak shaving, and valley filling, have been developed in order to solve congestion problems in the grid.

3.1.1 Congestion management

The concept of congestion in distribution systems typically appears when generation or demand exceeds the capacities of the installed equipment in the network, resulting in technical problems, such as overloading and power losses. Congestion management appears as a solution to deal with these issues [56]. It can be addressed in different manners, by using constrains for the thermal capacity of the installed equipment or establishing the capacity as an objective function. For instance, equation (1) represents a constraint to avoid overloads in lines; P_l and P_{lmax} are the power flow and thermal capacity of line l, respectively. In contrast to (1), (2) represents the total overload as a single objective function in which NL, LF_l, and L_{capl} are the number of lines, the power flow, and the thermal capacity of line l, respectively [57].

$$|P_l| \leq P_{lmax} \tag{1}$$

$$min \sum_{l=1}^{NL} (LF_l - L_{capl}) \tag{2}$$

TABLE III. CHARACTERISTICS OF THE REVIEWED PAPERS ON EV-DSS.

Ref.	Year	V2G	Solution technique	Uncert.	Test system	Centralized/ Decentralized	Software	Stackable
[91]	2012	–	Quadratic and linear programming	–	Adapted real system	C	Hybrid simulator/ CPLEX	N
[92]	2012	–	Linear programming	X	3-phase Real system	C	MATLAB	N
[62]	2014	–	Linear programming/ sub-gradient method	–	Adapted real system	C	–	N
[104]	2014	X	Constant-current and constant-voltage	–	–	–	PSIM (Powersim, Inc.)	Y
[105]	2014	X	Heuristics	–	–	–	MATLAB/Simulink	Y
[109]	2014	–	Convex optimization	–	10-bus test system	C	–	Y
[10]	2015	X	Heuristics	–	MV- distribution system	C	–	Y
[82]	2015	X	Heuristic: Fuzzy logic	–	Real test system, 1 main feeder and 4 sub-feeders	C	–	N
[84]	2015	–	Heuristics	–	3-phase Real system	D	MATLAB	Y
[121]	2015	X	Mixed-Integer Linear Programming	–	84-bus distribution test system	C	GAMS/CPLEX	Y
[77]	2015	X	Mixed-integer linear programming	–	37-bus distribution system	D	GAMS/CPLEX /MATLAB	N
[98]	2015	X	Constant current/reduced constant current (CC/RCC)	–	–	–	PSCAD/EMT	Y
[71]	2015	X	Mixed-integer non-linear programming	–	33-bus distribution system	–	GAMS	Y
[69]	2015	–	Quadratic program	–	3-phase real system	C/D	CPLEX	Y
[101]	2015	X	–	–	–	–	powersim (PSIM)	Y
[60]	2015	–	–	–	Adapted real system	C	JACK/MATALB/Simulink	N
[102]	2015	X	Non-linear programming	–	38-bus distribution system	C	MATLAB/Simulink	Y
[70]	2015	X	Self-adaptive evolutionary algorithm	–	69-bus distribution system	C	–	N
[123]	2015	X	Heuristics	–	70-bus Real distribution system	C	–	Y
[108]	2015	X	Fuzzy based control method	–	Real system	C	MATLAB/Simulink	N
[99]	2015	–	Heuristics	–	3-phase 33-bus distribution system	–	–	N
[87]	2015	–	Heuristics	–	–	D	MATLAB	N
[78]	2015	X	Heuristics	–	–	C	–	Y
[72]	2015	–	Linear programming	–	3-phase 134-bus distribution system	C	GAMS/CPLEX	Y
[75]	2015	X	Linear programming	–	–	D	–	N
[85]	2015	X	Heuristics	X	72-bus MV real test system	D	–	Y
[103]	2016	–	Droop control	–	3-phase real system	D	MATLAB/ SimPowerSystems	Y
[106]	2016	X	Mixed-integer non-linear programming / PSO-TVIW	–	33-bus test system	C	–	Y
[19]	2016	X	Stochastic global optimization problem approach/ Gaussian mixture model Copula function/Free Pattern Search	X	Real test system	C	–	Y
[81]	2016	X	Quadratic non-linear constrained optimization / sequential quadratic programming	–	Real test system	C/D	–	Y
[86]	2016	–	Linear programming	–	–	D	MATLAB	N
[83]	2016	X	–	–	–	–	–	N
[107]	2016	–	Particle Swarm Optimization	–	33-bus radial distribution system	C	–	Y
[64]	2016	–	Particle Swarm Optimization	–	449-bus network	C	MATLAB	Y
[96]	2016	X	Genetic Algorithms	–	Real system	C	–	Y
[63]	2016	X	Point Estimate Method	X	37-bus test system	C/D	MATLAB	Y
[100]	2016	X	Linear programming	–	–	–	–	N
[65]	2016	X	Quadratic optimization	–	Test system, 6 feeders, 53 LV buses	D	MATLAB	Y
[58]	2017	–	Droop control	–	3-phase real system	C/D	–	Y
[94]	2017	–	Droop control	–	3-phase test system	D	–	N
[9]	2017	X	Non-linear programming	–	3-phase - 123-bus distribution system	–	MATLAB/GAMS	Y
[61]	2017	–	Sample average/approximation Bender's decomposition	X	–	C	–	N
[59]	2017	X	Mixed-integer non-linear programming	–	37-bus distribution system	C	GAMS/CPLEX/CONOPT	Y
[122]	2017	–	Two-level stochastic Mixed-Integer Linear programming	X	15-bus distribution network	C	CPLEX	N
[93]	2017	–	Particle Swarm Optimization	–	134-bus LV residential distribution feeder	–	MATLAB/DigSILENT	N
[88]	2017	–	Heuristics	–	–	C	–	N
[89]	2017	X	Heuristics	X	Residential real system	D	–	N
[76]	2017	X	Mixed-integer linear programming	–	–	C	GAMS/CPLEX	N
[73]	2017	–	Heuristics	–	449-bus distribution system	C	C++	Y
[79]	2018	X	Genetic Algorithms	X	37-bus distribution system	C	–	Y
[110]	2018	X	Constant current/constant voltage (CC/CV) Droop control	–	10-bus-LV residential distribution system	C/D	PSCAD	Y
[80]	2018	–	Genetic Algorithms	X	69-bus test system	C	–	Y
[67]	2018	–	Gradient projection-based	–	5/12-feeder test system	D	–	Y
[95]	2018	–	mixed-integer linear programming	X	3-phase 178-bus distribution system	D	C++/AMPL/CPLEX	Y

Information not available (–), Centralized methods (C), Decentralized methods (D), Low Voltage Network (LV), Yes (Y), No (N)

Congestion management is addressed in [58]–[68]. In [58],

TABLE III. CHARACTERISTICS OF THE REVIEWED PAPERS ON EV-DSS. *(Continuation...)*

Ref.	Year	V2G	Solution technique	Uncert.	Test system	Centralized/ Decentralized	Software	Stackable
[111]	2018	–	Non-linear programming	–	33-bus distribution system	C	GAMS/KNITRO	Y
[124]	2018	–	mixed-integer linear programming	–	107-bus distribution system (11 MV and 96 LV)	C	AMPL/CPLEX	Y
[97]	2018	X	–	X	Real test system	C	–	Y
[74]	2018	X	Heuristics	–	Real distribution system	C	MATLAB/DigSILENT	Y
[68]	2018	–	linear programming	–	4-bus test system	D	GAMS/CPLEX	Y
[66]	2018	–	mixed-integer linear programming	X	33-bus distribution system	D	GAMS/CPLEX	Y
[90]	2018	–	Convex optimization	–	3-phase real distribution system	D	MATLAB/CVX	Y

Information not available (–), Centralized methods (C), Decentralized methods (D), Low Voltage Network (LV), Yes (Y), No (N)

the authors develop a smart charging controller that can be used for centralized/decentralized EV control, helping the grid with congestion and frequency issues. The authors in [64] develop an online algorithm for optimal EV charging coordination considering EV user preferences and grid technical conditions, contributing indirectly with loss minimization reduction.

In [67], a gradient projection-based method to deal with overloading on the transformers is proposed. Similarly, in [63], a probabilistic model is proposed to reduce the probability of congestion of lines and under/overvoltage in the nodes in a radial distribution network. The authors in [59] propose three different EV charging coordination algorithms to prevent line congestion, voltage drops, and transformer congestion. A similar approach can be found in [62], in which the congestion problem is addressed through a coordination strategy to minimize the charging cost of EVs while maintaining thermal limits and considering the EV user requirements.

In contrast to the studies described above, in [61], an EV charging coordination model is proposed to control the EV loads at a public station with fast chargers installed. The EV load is managed using its charging flexibility, so congestion problems are avoided. Moreover, in [66] and [68], price-based methods are proposed for congestion management in distribution networks under high penetration of EVs and heat pumps.

3.1.2 Loss minimization

Power losses are the energy dissipated as heat through the conductors. Typically, as demand increases, power losses increase as well. A classic formulation for minimizing the power losses in distribution systems is given by (3), where R_l and I_l are the resistance and the current of line *l*, respectively.

$$min \sum_{l}^{NL} R_l I_l^2 \quad (3)$$

The strategies developed in [69]–[72], [73], and [74] deal with power losses in the grid. A multi-objective methodology for the day-ahead active and reactive power scheduling problem is proposed in [71]. Here, EVs contribute with voltage regulation through active power control. In [72], the proposed online EV charging coordination minimizes the total cost of the electricity and the power losses, considering the network security, power quality, and EV constraints. Load shifting is implicitly addressed in this work.

Centralized and decentralized EV charging coordination strategies for balancing the operation of distribution networks using EV chargers and PV inverters are proposed in [69]. The objective function aims to minimize the load variance, dealing with power losses and avoiding the violation of voltage limits. Distinct from [69], in [70], the authors propose a stochastic optimization model to solve the distribution feeder reconfiguration problem as a reliability-enhancing strategy to coordinate the V2G provision of EV fleets. In [73], charging coordination strategies are proposed to minimize the total operational cost of the distribution system considering customer preferences and to maintain the technical grid constraints, while in [74], the strategies are developed to minimize variations in the average voltage of the feeders.

3.1.3 Load shifting

Load shifting reduces the utility loads during periods of peak demand and builds the load in off-peak periods, which means that some appliances (e.g., EVs) are switched off during peak demand [51]. As a result, the electricity consumption is shifted from peak to off-peak hours, and vice versa.

Several studies have involved load-shifting strategies for minimizing the peak demand. For instance, in [75], the authors propose distributed algorithms that enable EV users to participate in demand response programs to reduce the peak demand and to flatten the demand curve through a game theory approach. Similarly, an intelligent algorithm to control EV charging/discharging is proposed in [76]. There, the algorithm takes advantage of the energy store capacity of EVs to provide support to the grid and avoids new peak demands by using a tariffs scheme.

The work presented in [77] proposes a mathematical model in which the EV load is shifted according to the charging prices, and the profit of all the involved parties is maximized. In the same way, in [78], an EV charging/discharging control for load leveling to minimize the electricity cost is proposed. The methodology is developed for peak-load shifting by using the EV batteries and PV panels to support electricity in a small-scale energy management system. In [79] and [80], smart charging strategies are proposed to deal with peak loads through load shifting. Although [79] considers the technical constraints of the grid and the EVs, [80] is more focused on economical solutions for future smart cities.

3.1.4 Peak shaving and valley filling

Peak shaving consists of the peak demand reduction of the system by direct load control, while valley filling is another form of load management, which embraces building load in off-peak periods and improving the load factor [51]. In terms of EVs, users are encouraged to charge their cars during the off-peak periods. Basic formulations for these services are presented in (4) and (5).

$$\min \sum_{n=1}^{N} C_n \Delta P_{lcn} \quad (4)$$

$$\max \sum_{t \epsilon T_{off-peak}} P_t \quad (5)$$

In (4), the total curtailed load cost is minimized, where N is the number of loads to be disconnected, C_n is the cost of each load, and ΔP_{lcn} is the quantity of load curtailed. In (5), the power consumed from the grid at time t (P_t) during the off-peak periods ($T_{off-peak}$) is maximized.Several works have been developed in order to provide peak shaving and valley filling services [81]–[83]. Alternatively, [19], [84], and [85] only apply peak shaving, while in [86], [87], [88], [89], and [90], only valley filling is considered. In [82], the authors design fuzzy logic controllers to be used in the substations and in the EV charging stations for real-time EV charging coordination to support the grid. In [81] and [85], distributed EV charging strategies are proposed to minimize the system load variance and to flatten the daily grid demand. While [81] focuses on the EV/RES coordination, [85] focuses on the EV owners' preferences. A similar approach can be found in [83], in which an algorithm for EV charging/discharging coordination is proposed to minimize the peak load demand and to foresee congestion in the feeders and transformers. In [90], a strategy to coordinate the available PEV battery capacity for local peak shaving, along with a peak-shaving index, are proposed.

The work presented in [19] proposes an approach for the statistical assessment of the potential of plug-in EV fleets providing ancillary services using V2G technology. In [86], decentralized algorithms with minimal communication and delay considerations are proposed to prevent overloading in transformers and to achieve a desirable level of valley filling in the grid. Likewise, in [87], the authors propose strategies for solving the EV charging coordination problem, considering the EV owners' preferences while minimizing the variance and peak of the aggregated load profile. In [88], the authors propose a valley filling strategy for EV charging coordination that can improve the grid operation with a low computational algorithm, while in [89], EV charging/discharging control strategies are proposed using a predictive control approach to reduce power fluctuations from EV charging and their impact on the demand curve. In [89], the EV load is managed in the valley filling operation, similar to the approach proposed in [67]. Additionally, the works presented in [19], [84], and [81] contribute indirectly with loss minimization and voltage regulation.

3.1.5 Voltage regulation by active power control

Voltage issues appear when connecting generation or consumption units to the distribution network, leading to voltage rise or drop problems. Active and reactive voltage control methods have been developed to deal with these problems by controlling different network resources, such as on-load tap changers, distributed generation units, capacitor banks, and other controllable devices (e.g., EVs). Voltage control can be carried out using constraints for voltage limits as described in (6), where V_i, V_i^{min}, and V_i^{max} are the voltage magnitude and the minimum and the maximum voltages at node *i*, respectively. It can also be formulated as an objective function in which the total voltage deviation, i.e., difference between a voltage reference and an estimated value, is minimized, as described in (7). N_{bus}, $V_{i,r}$, and V_i are the number of nodes, the voltage reference, and the estimated voltage at note *i*, respectively.

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (6)$$

$$\min \sum_{l=1}^{Nbus} \left(V_{i,r} - V_i\right)^2 \quad (7)$$

Voltage regulation has been addressed in [9], [65], [91]–[94], and [95]. In [9], a methodology for EV and PV coordination in real-time is developed in order to mitigate the imbalance in low voltage (LV) distribution grids by using V2G. In [9], demand response is used as a strategy to cope with peak demand and voltage drop issues. The study in [91] aims at minimizing the total EV charging cost, considering the interaction between the aggregator, the DSO, and the electricity market, while maintaining the technical conditions of the grid. In the same way, control algorithms are proposed in [92] to optimize the EV charging coordination, maximize the power required for each EV, and maintain the grid operational constraints.

A method for optimal EV charging/discharging coordination to improve the voltage imbalance factor is proposed in [93], while the authors in [94] develop a methodology to improve the power quality of a low voltage network. A local smart charging controller is used for validating the EVs' ability to reduce voltage imbalances by modulating their charging current according to local voltage measurements. Similarly, in [95], a novel method is proposed that only requires local voltage magnitude measurements to maintain the operational limits of the distribution system. A similar approach can be found in [65], in which an algorithm for managing EV charging/discharging in LV distribution networks is proposed. The objective function aims at controlling the voltage profile while considering the EV users' preferences. Furthermore, the algorithm reduces the line and transformer loadings during the peak hours in an indirect way. In [19], [58], [59], [71], [70], [81], [64], [96], [63], [80], and [97], the voltage regulation service is indirectly addressed as an active power support service.

Most of the studies that address services in the category of active power support consider V2G technology in their approaches. Nonetheless, it is not a requirement to offer this kind of service to the grid.

3.2 Reactive power services

Reactive power and voltage control can be properly managed and implemented to provide adequate service quality. Several works have demonstrated that reactive power control can be used to maintain the voltage within acceptable levels. It can also be used to reduce power losses and congestion issues and to improve the power factor and congestion.

3.2.1 Reactive power compensation

Reactive power compensation is a method for balancing the capacitive and inductive components of a power system in order to provide sufficient voltage support and to enhance the reliability and security of the grid. In terms of EVs, it is a service provided by the DC-link capacitor of an EV bidirectional battery charger, which, according to the literature, could be advantageous in terms of the life cycle of the battery because the battery is not directly responsible for providing this service [20]. Different studies addressing this topic can be found in [84], [98]–[108], and [109]. Furthermore, most of them also deal with issues related to voltage drops and power losses. For instance, in [84], despite the fact that the work is mainly focused on reactive power compensation, the methodology also deals with power loss issues. In that work, the authors propose three algorithms for EV charging and study the impact of the reactive power injection on the voltage deviation, peak load, and power losses. Similarly, in [109], a P-Q control strategy for EV charging stations is proposed, in which EVs are used to compensate the reactive power consumed by wind turbines installed at the distribution system level.

3.2.2 Reactive power compensation from EV chargers

Some works are focused on the EV chargers. For instance, in [98], the authors design a bidirectional EV fast charger that is used to provide reactive power compensation by maintaining voltage regulation and power factor correction. Similarly, in [101] and [110], the authors implement a single-phase on-board bidirectional EV charger, which not only provides energy to the EV batteries, but also provides reactive power support to the grid. In the same way, a control strategy for EV charging and reactive power support using a three-phase off-board EV charger is developed in [104], while in [105], the authors propose a reactive power compensation method for EVs in which the power limit of the system is controlled by establishing an active power priority. An alternative approach is proposed in [102], in which the authors develop an optimal coordinated voltage regulation algorithm including EV, DG, and on-load tap-changer devices. Alternatively, the work in [103] proposes an EV reactive power control, dependent on the voltage. The objective aims to support the loaded phases and mitigate the voltage imbalances of the grid without affecting user comfort.

3.2.3 Smart charging/discharging strategies

Distinct from the aforementioned works, a smart charging/discharging strategy of EV aggregators is developed in [106] to provide services to the grid within an energy management system. A similar approach can be found in [107], in which the authors propose an algorithm for continuous reactive power management by EVs and PV systems, considering technical aspects of the network. Similar results can be found in [99], in which a reactive power management strategy is proposed.

In [108], a grid-supporting EV station is modeled, and the EVs provide active and reactive power support to the grid by controlling the power angle and voltage. The approach in [100] evaluates the capability and cost of providing reactive power support by EVs through a mathematical model that considers the grid's technical constraints and EV user requirements. In [111], voltage control is addressed by managing the reactive power from EVs. A mathematical model is proposed to minimize EV load curtailment, power losses, and load shifting in an implicit way.

Regarding voltage control services, most of the previous studies that address reactive power compensation implicitly address voltage issues, as previously mentioned.

3.3 Grid integration of RES

Along with EVs, RES integration into distribution systems is emerging as a solution to cope with environmental issues. However, it has been demonstrated that a high penetration of RES may cause operational problems to the grid due to its intermittency, bringing additional challenges for DSOs [112].

The joint operation of EVs and RES is a good option for DSOs to deal with these issues. EVs can support the grid operation in different ways, taking into account that some EV-DSS, for instance, are inspired in the services provided by DG units and energy storage devices to TSOs. The services included in this category refer to those in which EVs help to support the integration of RES into the grid by mitigating the intermittent output power from solar energy (PV) or wind energy (WE). EV energy consumption is encouraged during the periods of high RES power production in order to avoid power curtailments. Moreover, when properly managed, EVs can act as storage devices to satisfy the demand when there is a deficit in the power production from RES.

Regarding the services provided by EVs for supporting RES integration into distribution systems, a number of studies examine the large-scale integration of EVs for supporting the integration of WE [113] and PV in power systems [114]–[116]. Despite the fact that WE is usually integrated into the transmission systems, the penetration of wind power at the distribution system level has also been studied in [117], in which demand response strategies are proposed to prevent overvoltage issues. In contrast, solar energy is usually integrated at the distribution system level, at which overvoltage issues are also addressed [118], [119].

3.3.1 Joint operation of EVs, WE, and PV systems

Several approaches have focused on the joint operation of EVs and RES. In [34] and [120], reviews related to the ability of EVs to support RES integration into the distribution system, as well as its economic and environmental impacts, are presented. The work presented in [10] proposes an algorithm for controlling EV charging/discharging to deal with the high penetration of RES. The algorithm considers wind turbines at the medium voltage (MV) level and solar panels at the LV level, and it uses EVs for the grid support, dealing mainly with voltage deviation issues. Similarly, in [121], the authors propose a method for EV charging coordination, in which the EVs are considered responsive loads that can provide reserve services to the grid in order to compensate for renewable power production variability (WE and PV systems). Another approach is proposed in [122], in which a mathematical model is developed to manage the integrated operation of both plug-in EV parking lots and RES. In this work, the technical constraints of the distribution network are partly taken into account.

3.3.2 Joint operation of EVs and PV systems

The authors in [123] develop a control strategy for EV charging/discharging to mitigate PV system impacts: overvoltage during the day, peak load during the evening, and reverse power flows. Similar strategies are proposed in [97], aiming at reducing the PV power curtailment caused by overvoltages under vehicle-to-home scenarios. In the same way, in [96], an algorithm for managing the integrated operation of EVs and PV systems by using EVs as storage devices is proposed. The objective is to maximize the participation of PV systems in ancillary services by using EV storage, considering the EV user requirements and the grid constraints. The storage also can help to deal with the peak load at night. In [114]–[116] and [124], storage devices are also included within the operational strategies for EVs and RES.

Even though the approaches in [9], [78], [107], and [109] were described in previous sections, they also address the joint management of EVs and RES in order to improve the operation of the grid.

3.4 Limitation/Weakness of the reviewed works and research requirements

It is clear that most of the previous papers are focused on developing optimal strategies and methods to control the EV charging coordination, aiming to minimize/maximize different objectives named in this manuscript as EV-DSS. However, it could be observed from the literature review that important aspects within the strategies are disregarded or even developed based on unrealistic assumptions, making the implementation of EV-DSS in real-life applications difficult.

3.4.1 Price-based strategies in active power control

Most of the services regarding active power support deal with load congestion and peak demand issues, which may be influenced by price signals and uncontrollable elements, such as socioeconomic and environmental factors. These issues typically appear during the peak hours when not only is the conventional demand consumed, but, at the same time, EVs are being charged. Different strategies can be used for grid congestion management, such as distribution grid capacity market, advance capacity allocation, and dynamic tariffs [112], [125]. Most of the strategies for grid congestion management, for instance, are based on the electricity price behavior, and their main objective is encouraging the energy consumption of EVs during off-peak hours, when the electricity price is lower. In this context, the grid congestion management based on dynamic tariffs provides indirect service to the grid. However, these strategies should be carefully addressed in order to avoid creating new technical problems.

In terms of the peak demand, for example, one must bear in mind that peak hours do not only take place when the electricity price is high. For instance, in distribution systems with a high penetration of RES, the market may face negative prices (low prices) during the daytime. This may result in new peak hours and new technical issues, such as overloading in some feeders or undervoltage problems in some nodes, although the

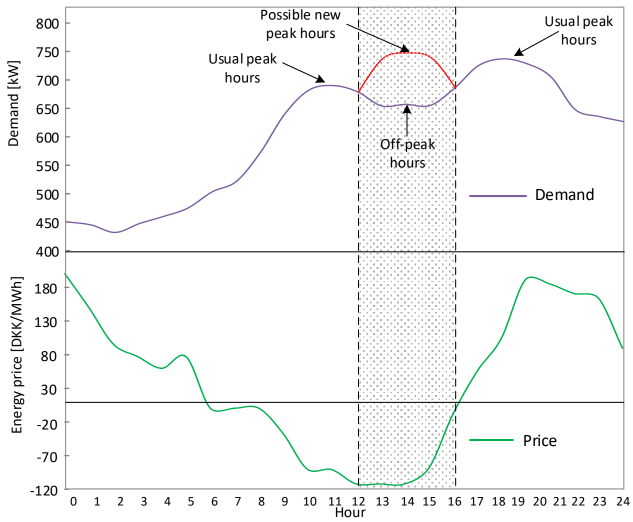


Fig. 4. Retail price and load for one day in Denmark.

*Price for May 1, 2017 [155]

electricity price is still low. For example, Fig. 4 shows a case in Denmark in which the electricity prices reached negative values in the off-peak hours (12:00 – 16:00) during the daytime on May 1, 2017. Lower prices could create new peaks if people are encouraged to charge their EVs during those hours, induced by the RES power production. Therefore, shifting the load to periods with lower electricity prices may be achieved at the expense of creating new peak demands. In the reviewed literature, some of the price-based signal strategies for EV charging/discharging coordination are focused on minimizing operational costs or EV charging costs. Although most of the works consider the technical constraints of the grid, the creation of new peaks is scarcely addressed. Therefore, price-based strategies in active power control should be carefully designed because new and potentially inconvenient peaks may be created.

3.4.2 Strategies for joint management of EVs and RES.

One way to deal with load congestion and new peak issues is properly managing the joint operation between EVs and RES, which could bring several advantages for DSOs. In the case of PV systems, for instance, it is known that their high penetration in distribution systems may cause new issues for the grid. Congestion, for example, can happen due to a high load or high power production of PVs. Then, DSOs may face overvoltage/undervoltage in some nodes or overloading in the transformers. However, EVs can help to alleviate those problems and to maintain the grid operation within reliable conditions. During the period of high PV production, the EVs can increase charging, even if the price of the electricity is high. In that case, EVs would help with the integration of PV systems into distribution systems by preventing the curtailment or, ultimately, the need of disconnection from the grid. Furthermore, if the EVs do not need to be charged during the periods of high PV production, they can be used as storage devices, as long as their batteries have available capacity, storing the surplus of energy coming from the PVs. This energy can be used during peak hours through V2G technology. There are few studies that consider this as a potential market for EV-

DSS, which affords room to propose new strategies for the integrated coordination between EVs and RES in distribution systems.

Although there is room for new investigations on the aforementioned topics, there is still one limitation that strongly affects the implementation of EV-DSS, which is the assumption of market existence for each service, as further discussed below.

3.4.3 Assumptions on market existence and economic calculations

Several important aspects, such as the existence of a market; regulations; or economic aspects, e.g., the cost related to these services, are assumed or simply disregarded in most of the literature reviewed. A figurative example is explained as follows: If a strategy is developed to coordinate the charging/discharging of EVs in order to minimize the charging cost from the owner's perspective, a contract between the owner and the other party (probably an aggregator or even the DSO) should exist. If the owner is willing to provide services for the DSO, how should the remuneration process be carried out? How should be the contract? How much can the owner earn for providing services for the DSO? How does the market work for each service? Many of these open questions have been addressed at the transmission system level. However, at the distribution system level, all of these topics remain unclear.

In this way, managing the charging/discharging control of EVs as a service for supporting the distribution grid becomes a new paradigm that requires an appropriate regulatory framework that endorses the EV service provision for DSOs [31]. By having a clear concept on it, the current strategies and methods developed to provide EV-DSS can be improved, or new ones can even be proposed to align with the current requirements for realistic implementations. Therefore, further research in market and economic aspects is required in order to ease the implementation of EV-DSS in real applications.

Based on the previous discussion, it can be seen that most of the literature reviewed remains in theoretical implementations. Thus, it would be useful to assess how far the EV-DSS are from being implemented in real applications. Hence, in the following section, an assessment of the maturity of EV-DSS is provided.

IV. Assessment of the Maturity of EV-DSS for Real Applications

Based on the background, it is clear that there are many strategies and solutions suggested for EV-DSS. However, since EV-DSS are a new paradigm, DSOs are not yet allowed to acquire services from other stakeholders or to participate in the market. Therefore, it is relevant to assess the implementability of these services in real applications and the possibility of being combined with frequency regulation as a special case. This is done by aiming at encouraging the development of local DSO markets and promoting the active participation of EVs as service providers for DSOs. The base case of frequency controlled normal operation reserve (FNR found in Denmark zone DK2) provided by EVs to the TSOs used for this comparison framework is supported by the real implementation of EV services through the Parker project [24]. The definition of these two comparison parameters is presented as follows:

Implementability: Ease of implementation of EV-DSS in a time horizon when compared with the current implementation of a real-life case of FNR provided by EV to TSOs.

Stackability: Possibility of combining different services. For simplicity, the comparison will be carried out between the categories previously defined in Table II, using a special case of FNR with EV-DSS and the possibility of combining them.

4.1 Implementability

The implementability of the EV-DSS is assessed by taking into account three time horizons as shown in Fig. 5: short-term (0-2 years), medium-term (2-5 years), and long-term (over 5 years). The assessment considers aspects such as the information and capabilities that are expected to be available for their implementation, for instance, infrastructure, technology, policies, and market framework, among others.

From Fig. 5, it is possible to observe that FNR is a current service provided by EVs (here and now). However, one has to bear in mind that frequency regulation is a service procured by TSOs for which there is a complete market framework designed. Comparing this specific case of FNR with EV-DSS, it is possible to observe that, for instance, reactive power compensation is a service that could be implemented in a medium-long-term time horizon. Although new grid codes in Denmark include policies that allow EV chargers to provide reactive power to the grid [126], reactive power support cannot be implemented in the short-term because there is not yet any market for reactive power services. In addition, the majority of EV chargers are not able to control the reactive power at the connection point.

Congestion management, load shifting, peak shaving, and valley filling could be implemented between a short- and medium-term time horizon, as indicated by some real applications of these services in California, in which the load is shifted, based on EV tariffs [127], [128]. These kinds of services are easier to implement since they are based on controlling active power, for which there are more market framework proposals. However, the application of these services depends on the demand in each market. For this reason, there are still some challenges from the DSO market perspective that should be addressed to definitively establish these services as EV-DSS.

Voltage regulation by active power is in the medium-term time horizon since this is a high-level power quality indicator. Currently, monetary penalties are applied to network operators in case of voltage quality issues. Since there are no markets specifically developed for this service, voltage regulation by active power still needs time to develop an appropriate market structure and become a DSO service. Voltage regulation by reactive power control could be implemented in the medium-long-term time horizon. The grid codes allow EV chargers to provide reactive power, but special equipment capable of providing reactive power (which is not common in current EV chargers) should be specially designed. Some companies are working on implementing this technology on new EV chargers.

EVs + RES integration support for DSOs are services that

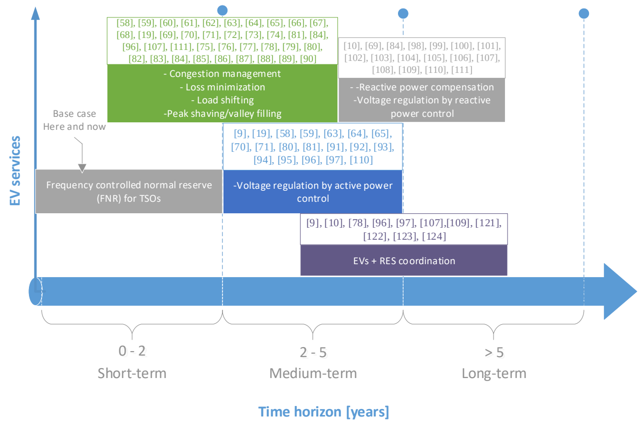


Fig. 5. Assessment of the maturity in the EV-DSS implementation.

could be implemented in the medium-long-term time horizon since there are already well-defined market frameworks for service provisions from RES to TSOs. These models can be used as a base to create new markets for the joint operation of EVs and RES as a DSO product. Moreover, there are some real implementations of services provided by RES. In Germany, for instance, peak reduction and voltage regulation services are being implemented through PV units connected to the distribution network in response to reduced grid tariffs [129]. However, the increasing penetration of PV units causes operational issues to the grid, resulting in grid expansion requirements. EVs can be used to support the integration of RES at the distribution system level under suitable regulations and market frameworks specifically developed or adjusted for such services. A lack of rules and standards for managing this technology and equipment in distribution grids makes it difficult to see the implementation of such services in the near future.

4.2 Stackability

The stackability of services is assessed using three levels: high, medium, and low (easy, medium, and difficult), considering two ways of application: scheduled or simultaneous. The possibility of a combination of EV-DSS per category with a special case of FNR and the possibility of combining between them are shown in Table IV. The last column in Table III provides information about the combination of different services in each paper included in the literature review.

The services in Table IV included in the category of active power support, such as congestion management, loss minimization, load shifting, peak shaving, and valley filling, can be easily combined with frequency regulation because these services are mainly constrained by time. This means that they are activated during specific periods of time, e.g., off-peak hours, according to the requirements of the distribution grid. Then, EVs can be used during the remaining time to provide other services, such as frequency regulation, assuming a minimum energy requirement per hour to satisfy the user preferences. However, the combination of these services is limited by the kind of time scheduling, e.g., in the day-ahead (scheduled), intra-day, or real-time (simultaneous). The high-level combination of these services only works if they are previously scheduled, because the power modulation is scheduled according to the peak or valley periods. Otherwise, the stackability of services is reduced because, in the intra-day or real-time market in which simultaneous services may be necessary, continuous power modulation is required. This hinders the combination of services because real-time information is needed, which requires special technology and equipment. Continuous power modulation implies that EVs should be ready at any time to provide specific services, which reduces the possibility of offering other services. A similar situation may occur with the combination between FNR and reactive power compensation, and between FNR and voltage regulation by reactive power control.

It is possible to see from Table IV that there is a high possibility of combination between FNR and RES integration support since these services also depend on time. EVs can be used during specific periods of time to mitigate the intermittent output power production from RES, and in the remaining time, they can be used to provide other services, such as frequency regulation. However, it could be more difficult to combine these services simultaneously, since frequency regulation requires constant power modulation, and the EV should be ready to provide the service at any time.

Reactive power compensation and voltage regulation by reactive power control could be combined, with most of the services belonging to the category of active power support, regardless of application. It is important to remember that this service is mainly limited by the requirement of special technology and equipment. Thus, it is possible to see that the reactive power provision is far from being implemented in the future, but would actually be mixable with the active power services for DSOs and TSOs.

The stackability of the services belonging to the category of active and reactive power support and to the category of RES integration support is high, as long as the services are prescheduled. This is because RES operation is constrained in time. Then, EVs can be used to support the grid when the RES operation is causing operational challenges, and in other periods of time, they can support the grid problems related to congestion, voltage drops, or overloading, e.g., caused by an increase in conventional demand. Stackability of these services in a simultaneous way is limited to the coincidence in time of operational problems caused by RES operation and those caused by other reasons, e.g., increase in conventional demand. For this reason, plus the demand for special equipment for information exchange in real-time, the stackability of these services qualifies for a medium level.

Despite the fact that some services can be executed simultaneously, prioritization and a sense of compromise should be accounted for between them. For instance, voltage regulation by active and reactive power can be combined with FNR; however, according to the system conditions, it should be defined which of those services has the highest priority.

V. CHALLENGES AND FUTURE RESEARCH SUGGESTIONS

TABLE IV. ASSESSMENT OF THE STACKABILITY OF THE EV-DSS PER CATEGORIES BASED ON THE PROPOSED CLASSIFICATION OF TABLE II.

	Scheduled				Simultaneous			
Category	FNR (Special case)	Active power support	Reactive power support	RES integration support	FNR (Special case)	Active power support	Reactive power support	RES integration support
Active power support	H	-	H	H	L	-	H	M
Reactive power support	H	-	-	H	L	-	-	M
RES integration support	H	-	-	-	L	-	-	-

H - High level, M - Medium level, L - Low level.

In this paper, a classification, summary, and comparison of the works addressing EV services specifically developed to support the distribution grid have been presented. Following the previous analysis, it can be concluded that, although there are certain works addressing EV-DSS, there are still key aspects that need to be tackled. An analysis of these key aspects can identify and highlight open challenges and needs for further research in specific areas to move toward realistic implementations of EV-DSS. In this way, challenges and prospects arising from the transition to a new perception of EV-DSS are discussed in this section.

5.1 Market framework

There are several market frameworks that are designed according to the requirements and regulations in each country. For instance, the market framework in the US is composed of generation companies, independent system operators (ISOs), and utility companies. In the US market framework, the ISO is the owner of the market. In Europe, the market framework is almost the same; the difference is that the market operator is independent [130]. Differences between market structures in several countries can be found in [26], [27]. According to the European Network of Transmission System Operators for Electricity (ENTSO-E) [131], there are available market frameworks for contemporary ancillary services provided to TSOs, such as frequency containment reserve capacity/energy, frequency restoration reserve capacity/energy (automatic), frequency restoration reserve capacity/energy (manual), and replacement reserves. The types of market frameworks in Europe are based on bilateral markets, free offers, hybrid markets, mandatory offers, mandatory provision, mandatory provision without reservation, and organized markets. In a bilateral market, for instance, a grid user and TSO negotiate a contract for the offered service and price/price system [131].

Regarding the market framework for EV-DSS, it could be mentioned that clearly, there is not much consensus regarding EV-DSS in the contemporary literature. At the moment, there is a market for frequency regulation services, but these services are usually required for TSOs. In contrast, at the distribution system level, there are market framework proposals for services such as congestion management and voltage regulation by using active power control [132], while for load shifting, peak shaving, and valley filling, they have not been proposed yet. Because there is no commercial market defined for reactive power support, the economic incentive is focused on active power support. Several works address loading and voltage regulation services by modulating the EV active power. Nonetheless, some EV users may not enable this service due to the delay in the charging process, which affects their comfort. Furthermore, the communication infrastructure and users' privacy become additional limitations in the service provision [31].

Regarding reactive power support, there is a high potential for using EVs to provide voltage regulation by injecting reactive power into the grid. One of the reasons for using EVs on that purpose is that reactive power does not affect the charging process of the EVs, which maintains user comfort. Few works have addressed reactive power control strategies [98], [100], [101], [103]–[105]. This is a new area that could be explored, despite some limitations, especially those related to the requirements of special chargers with V2G technology, along with a market framework.

In this way, from the market framework point of view, market design for EV-DSS is a potential topic for further research since most of the DSOs are not allowed yet to acquire services from other parties or to participate in the market [31]. New market models that enable active and reactive EV-DSS, such as load shifting, peak shaving, valley filling, voltage regulation, and reactive power control at the distribution system level, can be investigated and proposed to enforce the participation of DSOs in the market as an active player.

5.2 Economic aspects

According to the literature review, it could be mentioned that there is a lack of information in terms of the economic aspects of EV-DSS. Most of the studies focus on EV coordination in order to address loading and voltage issues, disregarding the details of the economic aspects, such as the revenues for providing services to the DSOs. One possible reason could be that these calculations depend highly on the regulation policies and socioeconomic and environmental conditions of each country. It is worth mentioning that the main incentive for the EV owners to allow active power control is the minimization of the EV charging cost. Usually, these strategies are based on electricity prices and involve the EVs being charged during periods of low electricity prices. However, most of the studies focus on developing strategies, methodologies, and algorithms for EV charging coordination while disregarding the economic aspects of EV-DSS.

One important issue regarding the economic aspects of EV-DSS is the definition of the price signals, so that the results benefit all stakeholders. The work presented in [133] proposes a market framework, introducing a design for an EV charging billing process based on a two-price model in order to incorporate EV services into distribution systems. According to the simulations carried out in [133] using a real distribution system in Denmark, one EV user does not receive much money per year for providing services to the DSOs, considering one single charging event per EV per day. It is important to mention that the estimation of the revenues for the DSOs is not easy to assess because there are several parties involved in the retail electricity market with a corresponding revenue distribution.

On the other hand, although there is not a market framework for service provision at the distribution system level, and even though there is no information regarding the economic aspects associated with them, a good starting point could be the inclusion of these services as part of the grid codes in the future. In Denmark, for instance, EV chargers should be able to provide reactive power to the grid [126].

For these reasons, more research on this topic is encouraged in an attempt to answer many questions that remain unanswered. For instance, who will be able to provide flexibility to the DSOs? How can consumers be encouraged to provide services while being profitable? How much may consumers earn by providing services for DSOs? How should the grid operating rules be modified to include EV-DSS? What should the regulation framework be? It is worth mentioning that the answers to these questions depend on each country and the special needs of each DSO. These matters have been poorly addressed in contemporary literature. Therefore, economic evaluations, including aspects such as benefit analysis for all stakeholders and possible remuneration strategies for service providers, are still open for research.

5.3 EV battery degradation caused by EV services

Because EVs can offer grid support by controlling the charging/discharging of their batteries, the operational strategies developed for this control may affect the battery life. Factors mainly related to the operation of the EV, such as charge transfer, charging rate, and average SOC, affect the battery life span. When providing services, there is a higher probability of incurring on more EV charge and discharge cycles, and the charging rate should be modulated according to the control signal, e.g., the frequency signal, which may reduce the life span of the battery. Hence, it is expected that service provision may have a detrimental impact on battery degradation.

Some studies have focused on this matter. In [5], the authors analyze the effect on the EV battery life caused by the grid support and propose measures to reduce these negative impacts. In [134], a battery degradation cost model is developed based on the cost incurred by EV users as a result of the charging/discharging activities associated with participation in V2G programs. A similar approach can be found in [135], in which only the battery discharging degradation cost is taken into account to calculate the effect of providing V2G services. The works presented in [136] and [137] also address the battery degradation effects caused by EV service provision. Therefore, the impact on battery degradation is an important issue that should be always considered and assessed within the strategies developed to provide EV-DSS, because the integration of battery degradation costs may change the charging/discharging strategies. Moreover, it is necessary to answer questions in regard to economic calculations: How much damage is caused by providing services? How is this damage compensated? Who is responsible for the payment? Hence, this topic becomes an interesting potential field for future research.

A comparison of the hourly energy exchanged (charged and discharged) of one EV with and without providing services can be seen in Fig. 6. Fig. 6a shows the possible conventional daily energy exchanged for one EV Nissan LEAF with a battery capacity of 24 kWh. Considering the average travel distance per day in Denmark, which is approximately 40km [138], it results in a daily energy consumption for driving of approximately 8 kWh. Furthermore, it is assumed that the EV is used for traveling to work and that it is connected in a residential area for charging, using a slow charger with power rated at 3.6 kW. Assuming an unknown initial SOC of the battery and also assuming that the charging process will only finish when the car is disconnected or fully charged (according to the user preferences) it can be seen from Fig. 6a that the energy discharged only depends on the energy required for driving and that the charging rate is stable. Fig. 6b shows the total energy exchanged per hour of the same EV Nissan Leaf providing FNR to Energinet, the TSO in Denmark, through an ENEL V2G charger with 10 kW of power rated capacity during one complete day (data from Parker [24], a project in which a real demonstration of FNR provided by an EV fleet in Denmark is being carried out [139]). It can be seen from Fig. 6b that during some hours (e.g., hour 1 and 4) there are energy charged and discharged at the same time. This is because the frequency signal is measured with one-second resolution, and due to its high fluctuation and uncertain behavior, the system may face over and under frequencies from one second to another. This may result in charging and discharging actions during the same hour, which means that the EV may consume or inject power from/to the grid during one hour.

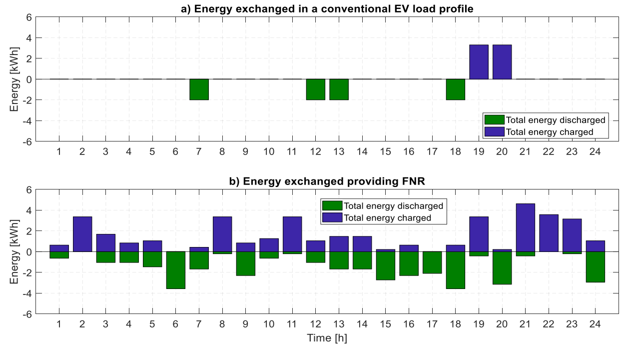


Fig. 6. Daily energy exchanged for one car.

The differences between the charging rates for both cases are depicted in Fig. 6. As can be seen, the energy exchanged in the EV transportation load profile is less than when the car is providing FNR services to the grid. It is worth mentioning that the amount of energy charged or discharged in the case of FNR fluctuates hour by hour. Since the energy exchanged is directly related to the depth of discharge of the battery, the service provision may result in more battery degradation.

5.4 Impacts of TSO service provision by EVs on distribution grids

Since TSOs are responsible for grid stability and security, TSOs are responsible for maintaining the balance between electricity consumption and production by procuring ancillary

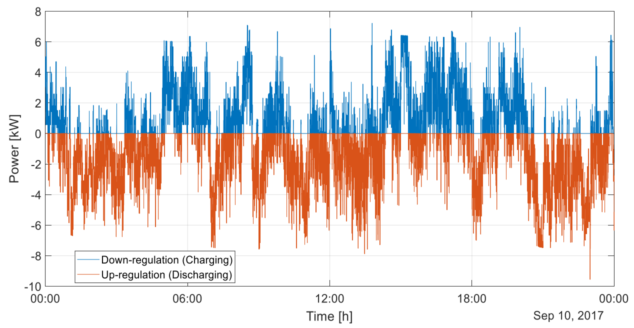


Fig. 7. Power fluctuation of one car during one complete day.

services, such as frequency and voltage regulation. Frequency regulation is one of the most common services procured by TSOs for grid balancing, and EVs are pointed out as a prominent option to provide this service due to the manageable nature of their loads, availability, bidirectional power capacity, and quick response time [140]. However, considering that the EVs are mainly connected to the distribution network, ancillary services provision for TSOs may affect the distribution grid to which EVs are connected; that automatically results in a conflict of interest between DSOs and TSOs [141], [142]. This topic has been scarcely studied in the literature; therefore, it deserves more attention, since EVs have been becoming more popular as new service providers in recent years.

The preliminary results from Parker [24] allow us to further discuss the possible conflicts between TSOs and DSOs. Fig. 7 shows the real operation of one EV (the same described in Fig. 6b) providing FNR to Energinet during one complete day. Fig. 7 depicts the power provided by the EV with one-second resolution in the case of over frequencies, where down-regulation is required and the charging mode is activated, and in the case of under frequencies, where up-regulation is required and the discharging mode is activated. As can be seen, high power fluctuations occur during the day, caused by the charging and discharging actions resulting from the frequency signals. On one hand, it has been already demonstrated that a high penetration of EVs in distribution systems causes detrimental impacts on the network. On the other hand, if this power fluctuation is extrapolated to a huge number of EVs connected at the distribution level, technical issues (e.g., overloading in the transformers, line congestion, voltage drops, or phase unbalances) are anticipated. Hence, the effect of this power fluctuation on the distribution grid should be taken into account when developing strategies for service provision by EVs to TSOs. In the same way, the fact that service provision from EVs to TSOs may cause conflicts between DSOs and TSOs leads us to anticipate that the service provision from EVs to DSOs will cause conflicts between DSOs and other stakeholders, such as aggregators, balance responsible parties, or even the end users (according to the market structure).

Considering the lack of strong research addressing this topic, and based on the preliminary results of the Parker project, it is possible to claim that further investigations on the conflicts that may arise from the EV service provision are required in an attempt to answer several open questions: How would DSOs be compensated for the operational problems caused by the TSO service provision? Who will pay for the damages caused in the distribution grid? Are there stacked services that can solve problems for different parties at the same time (for instance, DSOs and TSOs)? The answers to these questions can ease the implementation of DSO services in real applications.

5.5 Emerging EV technologies and their impact on distribution grids

EVs are part of different technologies involved in smart cities, especially those used to reduce green-house emissions and deal with environmental issues. Other emerging technologies, such as connected and autonomous vehicles, are being incorporated in smart cities as a way to deal with traffic and transportation issues. In a future transportation electrification scenario, the combination of these two technologies may bring potential benefits, but also challenges, in several aspects [143], [144]. Autonomous vehicles and EVs are complementary from a technology point of view [145]–[147]. For instance, EVs could be easier for auto driving due to the electric components [148].

Autonomous and connected EVs (ACEVs) may have the capability to manage many functionalities, such as SOC, the charging power, and the charging/discharging time, without deteriorating user comfort [144]. To this aim, ACEVs need to make use of communication tools, that allow them to find charging facilities. For instance, in [149], the authors develop a communication tool for vehicles to localize access points online with improved connectivity signals. Similarly, a methodology for the optimal allocation of wireless power transfer systems for autonomous EVs is presented in [150]. In [151], the authors develop a software that allows for communication between the database and a group of drones, which could be adapted for the operation of ACEV fleets. ACEVs may use similar technologies to manage energy functions in an automatized and optimized way and to enable communication between involved parties (e.g., ACEVs, users, operating system, transportation utilities, electricity companies, aggregators, etc.).

As a result, it is expected that ACEVs will be integrated in the power system due to their energy requirements, which may bring additional challenges to distribution systems. ACEVs' load will represent an increase in the energy demand, which may provoke operational problems with the grid, similar to those provoked by current EVs. However, the ACEVs' capabilities may be advantageous for DSOs or aggregators in terms of flexibility, since the charging/discharging of ACEVs could be more easily programmed using communication technologies to support the system operation through different DSO services. In this way, DSOs may cope with challenges arising from uncertain variables related to EV user behavior, since it is difficult to predict when and where a private EV owner will connect the car to charge its battery.

Few works have analyzed the impacts of the ACEVs' integration in power systems [144], [152], [153]. Moreover, similar to the current EVs, a large-scale implementation of ACEVs and the service provision to DSOs must still overcome many barriers related to the policies, agreements, infrastructure, and technology [146], [154]. Considering the growing penetration of emerging EV technologies and the lack of research in the context of DSO services, further investigations are required in this regard to pave the way toward an optimized integration of emerging EV technologies in distribution systems. Additionally, it is worth exploring the possibility of adapting the methods already proposed in the current literature (those developed to optimize the integration of EVs in the power system) to cope with the integration of ACEVs in distribution grids.

VI. Conclusions

This paper presented a review of the recent literature focusing on distribution system services provided by EVs (EV-DSS). It was found that there is not an agreement regarding the classification of the services provided by EVs for DSOs, which could be because of the novelty of the concept at the distribution level; therefore, a new classification of EV-DSS was proposed, including three main categories: active power support, reactive power support, and renewable energy source (RES) integration support. A description of the services, basic formulations, and the main contributions of the reviewed papers were presented. This information provided an overview of the traditional methods and allowed us to identify weaknesses in the control strategies as a means to encourage exploring new ones, aligned with the current requirements for the realistic implementation of services from EVs for DSOs.

Additionally, a comparison framework of the work developed in the academic research with a real-life application of EV services using a specific case of frequency regulation service was proposed. Using the proposed framework, it is possible to assess the implementability of EV-DSS, i.e., how far the EV-DSS are from being implemented, and the stackability of the EV-DSS, i.e., how easily EV-DSS services can be combined with frequency regulation and other potential services.

This information can help researchers to identify new potential areas of research that need to be addressed to move toward the realistic implementation of EV-DSS. It was found that active power services have a high chance of being implemented in the short-term, while reactive power compensation is a service that could be implemented in a medium-long-term time horizon because of the technical and market limitations. It was also found that most of the services belonging to the category of active power support can be highly combined with frequency regulation and with reactive power services under specific conditions. As a last step, a comprehensive discussion regarding the challenges and prospects of the EV-DSS was presented. It included key topics such as market framework design, economic assessment, battery degradation, and impacts of TSO service provision by EVs on distribution grids. It is concluded that, although there were certain strategies and solutions proposed to address EV-DSS, most of these strategies were far from being implemented in real applications because they fail on assuming possible roles for DSOs as an active market player or even assuming the existence of a market for each service. Considering these aspects within the EV-DSS strategies may significantly increase their implementation in real-life cases. Moreover, it may help to promote the active participation of EVs as a services provider for DSOs and to stimulate the creation of regulations, standards, and market framework for DSO services.

In addition, although most of the aspects that remain unclear for moving toward realistic implementations of EV-DSS are related to market and regulatory barriers, other important barriers may also exist, e.g., the impact on the distribution grid and battery degradation caused by the EV service provision to any party of the whole power system. Thus, these kinds of topics are suggested as future research directions associated with EV-DSS.

References

[1] M. S. Kumar and S. T. Revankar, “Development scheme and key technology of an electric vehicle: An overview,” Renew. Sustain. Energy Rev., vol. 70, no. July 2016, pp. 1266–1285, 2017.

[2] A. Dubey and S. Santoso, “Electric vehicle charging on residential distribution systems: Impacts and mitigations,” IEEE Access, vol. 3. pp. 1871–1893, 2015.

[3] J. Xiong, K. Zhang, Y. Guo, and W. Su, “Investigate the impacts of PEV charging facilities on integrated electric distribution system and electrified transportation system,” IEEE Trans. Transp. Electrif., vol. 1, no. 2, pp. 178–187, Aug. 2015.

[4] K. Zafred, J. Nieto-Martin, and E. Butans, “Electric vehicles - effects on domestic low voltage networks,” in 2016 IEEE International Energy Conference (ENERGYCON), 2016, pp. 1–6.

[5] G. Lacey, G. Putrus, and E. Bentley, “Smart EV charging schedules: supporting the grid and protecting battery life,” IET Electr. Syst. Transp., vol. 7, no. 1, pp. 84–91, 2017.

[6] E. Veldman and R. A. Verzijlbergh, “Distribution grid impacts of smart electric vehicle charging from different perspectives,” IEEE Trans. Smart Grid, vol. 6, no. 1, pp. 333–342, 2015.

[7] J. Quirós-Tortós, L. F. Ochoa, S. W. Alnaser, and T. Butler, “Control of EV charging points for thermal and voltage management of LV networks,” IEEE Trans. Power Syst., vol. 31, no. 4, pp. 3028–3039, 2016.

[8] H. N. T. Nguyen, C. Zhang, and A. Mahmud, “Optimal coordination of G2V and V2G to support power grids with high penetration of renewable energy,” IEEE Trans. Transp. Electrif., vol. 1, no. 2, pp. 188–195, 2015.

[9] E. Akhavan-Rezai, M. F. Shaaban, E. F. El-Saadany, and F. Karray, “Managing demand for plug-in electric vehicles in unbalanced LV systems with photovoltaics,” IEEE Trans. Ind. Informatics, vol. 13, no. 3, pp. 1057–1067, Jun. 2017.

[10] R. A. Kordkheili, B. Bak-Jensen, J. R. Pillai, M. Savaghebi, and J. M. Guerrero, “Managing high penetration of renewable energy in MV grid by electric vehicle storage,” in 2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST), 2015, pp. 127–132.

[11] J. Lin, J. J. Q. Yu, K.-C. Leung, and V. O. K. Li, “Optimal scheduling with vehicle-to-grid ancillary services,” Energy Syst. Electr. Hybrid Veh., vol. 2, p. 395, 2016.

[12] C. Le Floch, E. Kara, and S. Moura, “PDE Modeling and control of electric vehicle fleets for ancillary services: A discrete charging case,” IEEE Trans. Smart Grid, 2016.

[13] M. Hou, Y. Zhao, and X. Ge, “Optimal scheduling of the plug-in electric vehicles aggregator energy and regulation services based on grid to vehicle,” Int. Trans. Electr. Energy Syst., vol. 27, no. 6, pp. 1–12, 2017.

[14] S. I. Vagropoulos, D. K. Kyriazidis, and A. G. Bakirtzis, “Real-time charging management framework for electric vehicle aggregators in a market environment,” IEEE Trans. Smart Grid, vol. 7, no. 2, pp. 948–957, 2016.

[15] J. Tomić and W. Kempton, “Using fleets of electric-drive vehicles for grid support,” J. Power Sources, vol. 168, no. 2, pp. 459–468, 2007.

[16] G. Wenzel, M. Negrete-Pincetic, D. E. Olivares, J. MacDonald, and D. S. Callaway, “Real-time charging strategies for an electric vehicle aggregator to provide ancillary services,” IEEE Trans. Smart Grid, vol. In press, pp. 1–1, 2017.

[17] K. Knezović, M. Marinelli, P. Codani, and Y. Perez, “Distribution grid services and flexibility provision by electric vehicles: A review of options,” in Proc. Universities Power Eng. Conf., 2015.

[18] J. Hu, H. Morais, T. Sousa, and M. Lind, “Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects,” Renew. Sustain. Energy Rev., vol. 56, pp. 1207–1226, 2016.

[19] S. Sarabi, A. Davigny, V. Courtecuisse, Y. Riffonneau, and B. Robyns, “Potential of vehicle-to-grid ancillary services considering the uncertainties in plug-in electric vehicle availability and service/localization limitations in distribution grids,” Appl. Energy, vol. 171, pp. 523–540, 2016.

[20] K. M. Tan, V. K. Ramachandaramurthy, and J. Y. Yong, “Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques,” Renew. Sustain. Energy Rev., vol. 53, pp. 720–732, 2016.

[21] N. Shaukat, B. Khan, S. M. Ali, C. A. Mehmood, J. Khan, U. Farid, M. Majid, S. M. Anwar, M. Jawad, and Z. Ullah, “A survey on electric vehicle transportation within smart grid system,” Renew. Sustain. Energy Rev., vol. 81, pp. 1329–1349, 2018.

[22] L. Rubino, C. Capasso, and O. Veneri, “Review on plug-in electric vehicle charging architectures integrated with distributed energy sources for sustainable mobility,” Appl. Energy, vol. 207, pp. 438–464, 2017.

[23] K. Mahmud, G. E. Town, S. Morsalin, and M. J. Hossain, “Integration of electric vehicles and management in the internet of energy,” Renew. Sustain. Energy Rev., vol. 82, pp. 4179–4203, 2018.

[24] “DANMARK, NISSAN NEWSROOM. Nissan, Enel and Nuvve operate world’s first fully commercial vehicle-to-grid hub in Denmark,” 2016. [Online]. Available: https://newsroom.nissan-europe.com/dk/da-dk/media/pressreleases/149191. [Accessed: 19-Nov-2017].

[25] E. Hirst and B. Kirby, Ancillary services. Oak Ridge, Tennessee: Oak Ridge National Laboratory, 1996.

[26] Y. G. Rebours, D. S. Kirschen, M. Trotignon, and S. Rossignol, “A survey of frequency and voltage control ancillary services - Part I: Technical features,” IEEE Trans. Power Syst., vol. 22, no. 1, pp. 350–357, 2007.

[27] Y. G. Rebours, D. S. Kirschen, M. Trotignon, and S. Rossignol, “A survey of frequency and voltage control ancillary services - Part II: Economic features,” IEEE Trans. Power Syst., vol. 22, no. 1, pp. 358–366, 2007.

[28] R. A. Verzijlbergh, M. O. W. Grond, Z. Lukszo, J. G. Slootweg, and M. D. Ilic, “Network impacts and cost savings of controlled EV charging,” IEEE Trans. Smart Grid, vol. 3, no. 3, pp. 1203–1212, 2012.

[29] J. García-Villalobos, I. Zamora, J. I. San Martín, F. J. Asensio, and V. Aperribay, “Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches,” Renew. Sustain. Energy Rev., vol. 38, pp. 717–731, 2014.

[30] T. Sousa, T. Soares, H. Morais, R. Castro, and Z. Vale, “Simulated annealing to handle energy and ancillary services joint management considering electric vehicles,” Electr. Power Syst. Res., vol. 136, pp. 383–397, 2016.

[31] K. Knezović, M. Marinelli, A. Zecchino, P. B. Andersen, and C. Traeholt, “Supporting involvement of electric vehicles in distribution grids: Lowering the barriers for a proactive integration,” Energy, vol. 134, pp. 458–468, 2017.

[32] RTE, “Report on the balancing mechanism: August 2015.” Réseau de transport d’électricité, 01-Aug-2015.

[33] J. Jefferson, A. Saldanha, J. Jefferson, A. Saldanha, E. Machado, A. Paula, C. De Mello, A. Paula, and C. De Mello, “Control strategies for smart smart charging discharging of plug-in electric vehicles,” in World’s largest Science , Technology & Medicine Open Access book publisher, InTech., I. N. Da Silva and R. Andrade Flauzino, Eds. InTech, 2016.

[34] M. Ghofrani, E. Detert, N. N. Hosseini, A. Arabali, N. Myers, and N. Phasith, “V2G Services for renewable integration,” in Modeling and Simulation for Electric Vehicle Applications, M. A. Fakhfakh, Ed. InTech, 2016.

[35] Z. Li, M. Chowdhury, P. Bhavsar, and Y. He, “Optimizing the performance of vehicle-to-grid (V2G) enabled battery electric vehicles through a smart charge scheduling model,” Int. J. Automot. Technol., vol. 16, no. 5, pp. 827–837, 2015.

[36] M. Leo, K. Kavi, H. Anders, and B. Moss, “Ancillary service revenue opportunities from electric vehicles via demand response,” 2011.

[37] E. Sortomme and M. A. El-Sharkawi, “Optimal scheduling of vehicle-to-grid energy and ancillary services,” IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 351–359, 2012.

[38] A. Janjic and L. Z. Velimirovic, “Optimal scheduling of utility electric vehicle fleet offering ancillary services,” ETRI J., vol. 37, no. 2, pp. 273–282, 2015.

[39] M. Ansari, A. T. Al-Awami, E. Sortomme, and M. A. Abido, “Coordinated bidding of ancillary services for vehicle-to-grid using fuzzy optimization,” IEEE Trans. Smart Grid, vol. 6, no. 1, pp. 261–270, Jan. 2015.

[40] Z. Zhou, C. Sun, R. Shi, Z. Chang, S. Zhou, and Y. Li, “Robust energy scheduling in vehicle-to-grid networks,” IEEE Netw., vol. 31, no. 2, pp. 30–37, 2017.

[41] D. R. Melo, A. Trippe, H. B. Gooi, and T. Massier, “Robust electric vehicle aggregation for ancillary service provision considering battery aging,” IEEE Trans. Smart Grid, vol. 9, no. 3, pp. 1728–1738, 2018.

[42] M. Vahedipour-Dahraie, H. Rashidizaheh-Kermani, H. Najafi, A. Anvari-Moghaddam, and J. Guerrero, “Coordination of EVs participation for load frequency control in isolated microgrids,” Appl. Sci., vol. 7, no. 6, pp. 1454–5101, 2017.

[43] M. F. M. Arani and Y. Mohamed, “Cooperative control of wind power generator and electric vehicles for microgrid primary frequency regulation,” IEEE Trans. Smart Grid, p. (To be published), 2017.

[44] M. H. Khooban, “Secondary load frequency control of time-delay stand-alone microgrids with electric vehicles,” IEEE Trans. Ind. Electron., vol. 65, no. 9, pp. 7416–7422, 2018.

[45] M. H. Khooban, T. Niknam, M. Shasadeghi, T. Dragicevic, and F. Blaabjerg, “Load frequency control in microgrids based on a stochastic noninteger controller,” IEEE Trans. Sustain. Energy, vol. 9, no. 2, pp. 853–861, 2018.

[46] P. Palensky and D. Dietrich, “Demand side management: Demand response, intelligent energy systems, and smart loads,” IEEE Trans. Ind. Informatics, vol. 7, no. 3, pp. 381–388, 2011.

[47] M. Zhou, Y. Gao, and G. Li, “Study on improvement of available transfer capability by demand side management,” in 2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, 2008.

[48] T. Logenthiran, D. Srinivasan, and T. Z. Shun, “Demand side management in smart grid using heuristic optimization,” IEEE Trans. Smart Grid, vol. 3, no. 3, pp. 1244–1252, 2012.

[49] Federal energy regulatory commision, “Assessment of demand response and advanced mitering,” 2010.

[50] C. Vivekananthan, Y. Mishra, G. Ledwich, and F. Li, “Demand response for residential appliances via customer reward scheme,” IEEE Trans. Smart Grid, vol. 5, no. 2, pp. 809–820, 2014.

[51] C. W. Gellings, “The concept of demand-side management for electric utilities,” Proc. IEEE, vol. 73, no. 10, pp. 1468–1470, 1985.

[52] S. Saini, “Demand-side management module,” Sustain. Energy Regul. Policymaking Africa, pp. 1–100, 2007.

[53] “ABB.” [Online]. Available: http://new.abb.com/substations/energy-storage-applications/load-leveling. [Accessed: 18-Jul-2017].

[54] D. S. Carr, “Lead/acid batteries in U.S.A. load-levelling applications,” J. Power Sources, vol. 31, no. 1, pp. 297–310, 1990.

[55] J. Quirós-Tortós, L. F. Ochoa, and B. Lees, “A statistical analysis of EV charging behavior in the UK,” in 2015 IEEE PES Innovative Smart Grid Technologies Latin America, ISGT LATAM 2015, 2016, pp. 445–449.

[56] A. N. M. M. Haque, P. H. Nguyen, W. L. Kling, and F. W. Bliek, “Congestion management in smart distribution network,” in 2014 49th International Universities Power Engineering Conference (UPEC), 2014, pp. 1–6.

[57] Dansk Energi; Universidad Carlos III de Madrid; Tampere University of Technology, “IDE4L: Deliverable 5.2/3: Congestion Management in Distribution Networks,” 2015.

[58] K. Knezović, S. Martinenas, P. B. Andersen, A. Zecchino, and M. Marinelli, “Enhancing the role of electric vehicles in the power grid: Field validation of multiple ancillary services,” IEEE Trans. Transp. Electrif., vol. 3, no. 1, pp. 201–209, 2017.

[59] J. Hu, H. Morais, T. Sousa, S. You, and R. D’Hulst, “Integration of electric vehicles into the power distribution network with a modified capacity allocation mechanism,” Energies, vol. 10, no. 2, 2017.

[60] J. Hu, A. Saleem, S. You, L. Nordström, M. Lind, and J. Østergaard, “A multi-agent system for distribution grid congestion management with electric vehicles,” Eng. Appl. Artif. Intell., vol. 38, pp. 45–58, 2015.

[61] F. Wu and R. Sioshansi, “A two-stage stochastic optimization model for scheduling electric vehicle charging loads to relieve distribution-system constraints,” Transp. Res. Part B Methodol., vol. 102, pp. 55–82, 2017.

[62] J. Hu, S. You, M. Lind, and J. Østergaard, "Coordinated charging of electric vehicles for congestion prevention in the distribution grid," IEEE Trans. Smart Grid, vol. 5, no. 2, pp. 703–711, 2014.
[63] J. Romero-Ruiz, J. Pérez-Ruiz, S. Martin, J. A. Aguado, and S. De La Torre, "Probabilistic congestion management using EVs in a smart grid with intermittent renewable generation," Electr. Power Syst. Res., vol. 137, pp. 155–162, 2016.
[64] S. Hajforoosh, M. A. S. Masoum, and S. M. Islam, "Online optimal variable charge-rate coordination of plug-in electric vehicles to maximize customer satisfaction and improve grid performance," Electr. Power Syst. Res., vol. 141, pp. 407–420, 2016.
[65] S. Mocci, N. Natale, F. Pilo, and S. Ruggeri, "Multi-agent control system for the exploitation of vehicle to grid in active LV networks," in CIRED Workshop 2016, 2016, pp. 1–4.
[66] Z. Liu, Q. Wu, S. S. Oren, S. Huang, R. Li, and L. Cheng, "Distribution locational marginal pricing for optimal electric vehicle charging through chance constrained mixed-integer programming," IEEE Trans. Smart Grid, vol. 9, no. 2, pp. 644–654, 2018.
[67] Z. Ma, N. Yang, S. Zou, and Y. Shao, "Charging coordination of Plug-In electric vehicles in distribution networks with capacity constrained feeder lines," IEEE Trans. Control Syst. Technol., vol. 26, no. 5, pp. 1917–1924, 2018.
[68] S. Huang and Q. Wu, "Dynamic subsidy method for congestion management in distribution networks," IEEE Trans. Smart Grid, vol. 9, no. 3, pp. 2140–2151, 2018.
[69] S. Weckx and J. Driesen, "Load balancing with EV chargers and PV inverters in unbalanced distribution grids," IEEE Trans. Sustain. Energy, vol. 6, no. 2, pp. 635–643, 2015.
[70] A. Kavousi-Fard, M. A. Rostami, and T. Niknam, "Reliability-oriented reconfiguration of vehicle-to-grid networks," IEEE Trans. Ind. Informatics, vol. 11, no. 3, pp. 682–691, 2015.
[71] T. Sousa, H. Morais, Z. Vale, and R. Castro, "A multi-objective optimization of the active and reactive resource scheduling at a distribution level in a smart grid context," Energy, vol. 85, pp. 236–250, Jun. 2015.
[72] M. Esmaili and A. Goldoust, "Multi-objective optimal charging of plug-in electric vehicles in unbalanced distribution networks," Int. J. Electr. Power Energy Syst., vol. 73, pp. 644–652, 2015.
[73] N. Banol Arias, J. F. Franco, M. Lavorato, and R. Romero, "Metaheuristic optimization algorithms for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation," Electr. Power Syst. Res., vol. 142, pp. 351–361, 2017.
[74] A. Hajizadeh and M. R. Kikhavani, "Coordination of bidirectional charging for plug-in electric vehicles in smart distribution systems," Electr. Eng., vol. 100, no. 2, pp. 1085–1096, 2018.
[75] F. Rassaei, W. S. Soh, and K. C. Chua, "Demand response for residential electric vehicles with random usage patterns in smart grids," IEEE Trans. Sustain. Energy, vol. 6, no. 4, pp. 1367–1376, 2015.
[76] M. A. Fotouhi Ghazvini, J. Soares, O. Abrishambaf, R. Castro, and Z. Vale, "Demand response implementation in smart households," Energy Build., vol. 143, pp. 129–148, 2017.
[77] M. A. López, S. De La Torre, S. Martín, and J. A. Aguado, "Demand-side management in smart grid operation considering electric vehicles load shifting and vehicle-to-grid support," Int. J. Electr. Power Energy Syst., vol. 64, pp. 689–698, 2015.
[78] M. Aziz, T. Oda, T. Mitani, Y. Watanabe, and T. Kashiwagi, "Utilization of electric vehicles and their used batteries for peak-load shifting," Energies, vol. 8, no. 5, pp. 3720–3738, 2015.
[79] R. Mehta, D. Srinivasan, A. M. Khambadkone, J. Yang, and A. Trivedi, "Smart charging strategies for optimal integration of plug-in electric vehicles within existing distribution system infrastructure," IEEE Trans. Smart Grid, vol. 9, no. 1, pp. 299–312, 2018.
[80] Y. Nie, X. Wang, and K. W. E. Cheng, "Multi-area self-adaptive pricing control in smart city with EV user participation," IEEE Trans. Intell. Transp. Syst., vol. 19, no. 7, pp. 2156–2164, 2018.
[81] E. L. Karfopoulos, K. A. Panourgias, and N. D. Hatziargyriou, "Distributed coordination of electric vehicles providing V2G regulation services," IEEE Trans. Power Syst., vol. 31, no. 4, pp. 2834–2846, 2016.
[82] M. Singh, K. Thirugnanam, P. Kumar, and I. Kar, "Real-time coordination of electric vehicles to support the grid at the distribution substation level," IEEE Syst. J., vol. 9, no. 3, pp. 1000–1010, 2015.
[83] M. A. Hussain and M. J. Lee, "Mobility incorporated vehicle-to-grid (V2G) optimization for uniform utilization in smart grid based power distribution network," in Smart Grid Inspired Future Technologies: First International Conference, SmartGIFT, 2017, pp. 3–15.
[84] N. Leemput, F. Geth, J. Van Roy, J. Büscher, and J. Driesen, "Reactive power support in residential LV distribution grids through electric vehicle charging," Sustain. Energy, Grids Networks, vol. 3, pp. 24–35, 2015.
[85] M. J. E. Alam, K. M. Muttaqi, and D. Sutanto, "A controllable local peak-shaving strategy for effective utilization of PEV battery capacity for distribution network support," IEEE Trans. Ind. Appl., vol. 51, no. 3, pp. 2030–2037, 2015.
[86] E. Ramos Muñoz, G. Razeghi, L. Zhang, and F. Jabbari, "Electric vehicle charging algorithms for coordination of the grid and distribution transformer levels," Energy, vol. 113, pp. 930–942, Oct. 2016.
[87] G. Binetti, A. Davoudi, D. Naso, B. Turchiano, and F. L. Lewis, "Scalable real-time electric vehicles charging with discrete charging rates," IEEE Trans. Smart Grid, vol. 6, no. 5, pp. 2211–2220, 2015.
[88] L. Jian, Y. Zheng, and Z. Shao, "High efficient valley-filling strategy for centralized coordinated charging of large-scale electric vehicles," Appl. Energy, vol. 186, pp. 46–55, 2017.
[89] W. Zhang, D. Zhang, B. Mu, L. Y. Wang, Y. Bao, J. Jiang, and H. Morais, "Decentralized electric vehicle charging strategies for reduced load variation and guaranteed charge completion in regional distribution grids," Energies, vol. 10, no. 2, 2017.
[90] M. C. Kisacikoglu, F. Erden, and N. Erdogan, "Distributed control of PEV charging based on energy demand forecast," IEEE Trans. Ind. Informatics, vol. 14, no. 1, pp. 332–341, 2018.
[91] O. Sundström and C. Binding, "Flexible charging optimization for electric vehicles considering distribution grid constraints," IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 26–37, 2012.
[92] P. Richardson, D. Flynn, and A. Keane, "Optimal charging of electric vehicles in low-voltage distribution systems," IEEE Trans. Power Syst., vol. 27, no. 1, pp. 268–279, 2012.
[93] H. F. Farahani, "Improving voltage unbalance of low-voltage distribution networks using plug-in electric vehicles," J. Clean. Prod., vol. 148, pp. 336–346, 2017.
[94] S. Martinenas, K. Knezović, and M. Marinelli, "Management of power quality issues in low voltage networks using electric vehicles: Experimental validation," IEEE Trans. Power Deliv., vol. 32, no. 2, pp. 971–979, 2017.
[95] J. E. Cardona, J. C. López, and M. J. Rider, "Decentralized electric vehicles charging coordination using only local voltage magnitude measurements," Electr. Power Syst. Res., vol. 161, pp. 139–151, 2018.
[96] R. Ahmadi Kordkheili, S. A. Pourmousavi, M. Savaghebi, J. M. Guerrero, and M. H. Nehrir, "Assessing the potential of plug-in electric vehicles in active distribution networks," Energies, vol. 9, no. 1, 2016.
[97] H. Kikusato, K. Mori, S. Yoshizawa, Y. Fujimoto, H. Asano, Y. Hayashi, A. Kawashima, S. Inagaki, and T. Suzuki, "Electric vehicle charge-discharge management for utilization of photovoltaic by coordination between home and grid energy management systems," IEEE Trans. Smart Grid, p. (To be published).
[98] J. Y. Yong, V. K. Ramachandaramurthy, K. M. Tan, and N. Mithulananthan, "Bi-directional electric vehicle fast charging station with novel reactive power compensation for voltage regulation," Int. J. Electr. Power Energy Syst., vol. 64, pp. 300–310, 2015.
[99] S. Pirouzi, M. A. Latify, and G. R. Yousefi, "Investigation on reactive power support capability of PEVS in distribution network operation," in ICEE 2015 - Proceedings of the 23rd Iranian Conference on Electrical Engineering, 2015, vol. 10, pp. 1591–1596.
[100] M. N. Mojdehi, M. Fardad, and P. Ghosh, "Technical and economical evaluation of reactive power service from aggregated EVs," Electr. Power Syst. Res., vol. 133, pp. 132–141, 2016.
[101] M. C. Kisacikoglu, M. Kesler, and L. M. Tolbert, "Single-phase on-board bidirectional PEV charger for V2G reactive power operation," IEEE Trans. Smart Grid, vol. 6, no. 2, pp. 767–775, 2015.
[102] M. A. Azzouz, M. F. Shaaban, and E. F. El-Saadany, "Real-time optimal voltage regulation for distribution networks incorporating high penetration of PEVs," IEEE Trans. Power Syst., vol. 30, no. 6, pp. 3234–3245, Nov. 2015.
[103] K. Knezović and M. Marinelli, "Phase-wise enhanced voltage support from electric vehicles in a Danish low-voltage distribution grid," Electr. Power Syst. Res., vol. 140, pp. 274–283, 2016.
[104] M. Kesler, M. C. Kisacikoglu, and L. M. Tolbert, "Vehicle-to-grid reactive power operation using plug-in electric vehicle bidirectional

offboard charger," IEEE Trans. Ind. Electron., vol. 61, no. 12, pp. 6778–6784, 2014.
[105] J. Gallardo-lozano, E. Romero-cadaval, S. Member, V. Miñambres-marcos, D. Vinnikov, T. Jalakas, and H. Hõimoja, "Grid reactive power compensation by using electric Vehicles," in 2014 Electric Power Quality and Supply Reliability Conference (PQ), 2014, pp. 19–24.
[106] M. P. Anand, S. Golshannavaz, W. Ongsakul, and A. Rajapakse, "Incorporating short-term topological variations in optimal energy management of MGs considering ancillary services by electric vehicles," Energy, vol. 112, pp. 241–253, 2016.
[107] O. Gandhi, W. Zhang, C. D. Rodríguez-Gallegos, D. Srinivasan, and T. Reindl, "Continuous optimization of reactive power from PV and EV in distribution system," in 2016 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia), 2016, pp. 281–287.
[108] K. Thirugnanam and P. Kumar, "Fuzzy based active and reactive power support to the distribution network using electric vehicles," in 2015 IEEE International Transportation Electrification Conference (ITEC), 2015, pp. 1–6.
[109] C. Wu, H. Akhavan-Hejazi, H. Mohsenian-Rad, and J. Huang, "PEV-based P-Q control in line distribution networks with high requirement for reactive power compensation," in 2014 IEEE PES Innovative Smart Grid Technologies Conference, ISGT 2014, 2014.
[110] M. Restrepo, J. Morris, M. Kazerani, and C. A. Cañizares, "Modeling and testing of a bidirectional smart charger for distribution system EV integration," IEEE Trans. Smart Grid, vol. 9, no. 1, pp. 152–162, 2018.
[111] J. Wang, G. R. Bharati, S. Paudyal, O. Ceylan, B. P. Bhattarai, and K. S. Myers, "Coordinated electric vehicle charging with reactive power support to distribution grids," IEEE Trans. Ind. Informatics, p. (To be published).
[112] B. Muruganantham, R. Gnanadass, and N. P. Padhy, "Challenges with renewable energy sources and storage in practical distribution systems," Renew. Sustain. Energy Rev., vol. 73, pp. 125–134, 2017.
[113] H. N. T. Nguyen, C. Zhang, and J. Zhang, "Dynamic demand control of electric vehicles to support power grid with high penetration level of renewable energy," IEEE Trans. Transp. Electrif., vol. 2, no. 1, pp. 66–75, 2016.
[114] J. Ugirumurera and Z. Haas, "Optimal sizing of a completely green charging system for electric vehicles," IEEE Trans. Transp. Electrif.
[115] Y. T. Liao and C. N. Lu, "Dispatch of EV charging station energy resources for sustainable mobility," IEEE Trans. Transp. Electrif., vol. 1, no. 1, pp. 86–93, 2015.
[116] D. Wu, H. Zeng, C. Lu, and B. Boulet, "Two-stage energy management for office buildings with workplace EV charging and renewable energy," IEEE Trans. Transp. Electrif., vol. 3, no. 1, pp. 225–237, 2017.
[117] S. Chalise, H. R. Atia, B. Poudel, and R. Tonkoski, "Impact of active power curtailment of wind turbines connected to residential feeders for overvoltage prevention," IEEE Trans. Sustain. Energy, vol. 7, no. 2, pp. 471–479, 2016.
[118] M. Karimi, H. Mokhlis, K. Naidu, S. Uddin, and A. H. A. Bakar, "Photovoltaic penetration issues and impacts in distribution network - A review," Renew. Sustain. Energy Rev., vol. 53, pp. 594–605, 2016.
[119] S. Hashemi and J. Østergaard, "Methods and strategies for overvoltage prevention in low voltage distribution systems with PV," IET Renew. Power Gener., vol. 11, no. 2, pp. 205–214, 2017.
[120] D. B. Richardson, "Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration," Renew. Sustain. Energy Rev., vol. 19, pp. 247–254, Mar. 2013.
[121] A. Zakariazadeh, S. Jadid, and P. Siano, "Integrated operation of electric vehicles and renewable generation in a smart distribution system," Energy Convers. Manag., vol. 89, pp. 99–110, 2015.
[122] M. Shafie-khah, P. Siano, D. Z. Fitiwi, N. Mahmoudi, and J. P. S. Catalão, "An innovative two-level model for electric vehicle parking lots in distribution systems with renewable energy," IEEE Trans. Smart Grid, vol. 9, no. 2, pp. 1506–1520, 2018.
[123] M. J. E. Alam, K. M. Muttaqi, and D. Sutanto, "Effective utilization of available PEV battery capacity for mitigation of solar PV impact and grid support with integrated V2G functionality," IEEE Trans. Smart Grid, vol. 7, no. 3, pp. 1562–1571, 2016.
[124] C. Sabillon, J. F. Franco, M. J. Rider, and R. Romero, "Joint optimal operation of photovoltaic units and electric vehicles in residential networks with storage systems: A dynamic scheduling method," Int. J. Electr. Power Energy Syst., vol. 103, pp. 136–145, 2018.
[125] P. Bach Andersen, J. Hu, and K. Heussen, "Coordination strategies for distribution grid congestion management in a multi-actor, multi-objective setting," in IEEE PES Innovative Smart Grid Technologies Conference Europe, 2012.
[126] ENERGINET, "Regulations for grid connection," Technical regulation 3.3.1 for battery plants, 2017. .
[127] Edison International Company, "Electric Vehicle Rates," Southern California, 2018. [Online]. Available: https://www.sce.com/wps/portal/home/residential/electric-cars/residential-rates/. [Accessed: 15-Jan-2018].
[128] San Diego Gas & Electric Company, "EV Rates," SDGE, 2016. [Online]. Available: https://www.sdge.com/clean-energy/ev-rates. [Accessed: 15-Jan-2018].
[129] E. Bayer, "Report on the German power system," Brussels, Belgium, 2015.
[130] T. V. Jensen, "Exploring market models for a european electricity grid with a high penetration of renewable energy sources," Technical University of Denmark, 2017.
[131] ENTSO-E, "Survey on ancillary services procurement and electricity balancing market design," 2017.
[132] C. Zhang, Y. Ding, N. C. Nordentoft, P. Pinson, and J. Østergaard, "FLECH: A Danish market solution for DSO congestion management through DER flexibility services," J. Mod. Power Syst. Clean Energy, vol. 2, no. 2, pp. 126–133, Jun. 2014.
[133] A. O. Gadea, "Technical investigation and economic assessment of DSO based services from electric vehicles," Technical University of Denmark, Risø, Roskilde, Denmark, 2017.
[134] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "A practical scheme to involve degradation cost of lithium-ion batteries in vehicle-to-grid applications," IEEE Trans. Sustain. Energy, vol. 7, no. 4, pp. 1730–1738, 2016.
[135] R. C. Leou, "Optimal charging/discharging control for electric vehicles considering power system constraints and operation costs," IEEE Trans. Power Syst., vol. 31, no. 3, pp. 1854–1860, 2016.
[136] D. Wang, J. Coignard, T. Zeng, C. Zhang, and S. Saxena, "Quantifying electric vehicle battery degradation from driving vs. vehicle-to-grid services," J. Power Sources, vol. 332, pp. 193–203, 2016.
[137] K. Darcovich, S. Recoskie, H. Ribberink, F. Pincet, and A. Foissac, "Effect on battery life of vehicle-to-home electric power provision under Canadian residential electrical demand," Appl. Therm. Eng., vol. 114, pp. 1515–1522, 2017.
[138] H. Christiansen and B. Z. Skougaard, "Documentation of the Danish National Travel Survey: DTU Transport," 2015.
[139] N. Banol Arias, S. Hashemi, P. Bach Andersen, C. Træholt, and R. Romero, "V2G Enabled EVs Providing Frequency Containment Reserves: Field Results," in 2017 IEEE Int. Conf. Ind. Technol (ICIT), 2018.
[140] E. Romero-Cadaval, F. Barrero-González, E. González-Romera, and M.-I. Milanés-Montero, "Using plug-in electric vehicles to implement ancillary services in smart distribution grids," in Plug In Electric Vehicles in Smart Grids: Integration Techniques, S. Rajakaruna, F. Shahnia, and A. Ghosh, Eds. Singapore: Springer Singapore, 2015, pp. 309–349.
[141] A. Zecchino, K. Knezović, and M. Marinelli, "Identification of conflicts between transmission and distribution system operators when acquiring ancillary services from electric vehicles," in 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe, 2017.
[142] H. Gerard, E. I. R. Puente, and D. Six, "Coordination between transmission and distribution system operators in the electricity sector: A conceptual framework," Util. Policy, vol. 50, pp. 40–48, 2018.
[143] D. Milakis, B. Van Arem, and B. Van Wee, "Policy and society related implications of automated driving: A review of literature and directions for future research," J. Intell. Transp. Syst. Technol. Planning, Oper., vol. 21, no. 4, pp. 324–348, 2017.
[144] R. Iacobucci, B. McLellan, and T. Tezuka, "Modeling shared autonomous electric vehicles: Potential for transport and power grid integration," Energy, vol. 158, pp. 148–163, 2018.
[145] D. Strugar, R. Hussain, M. Mazzara, V. Rivera, J. Lee, and R. Mustafin, "On M2M Micropayments: A case study of electric autonomous vehicles," Comput. Res. Repos., 2018.
[146] A. Nikitas, I. Kougias, E. Alyavina, and E. Njoya Tchouamou, "How can autonomous and connected vehicles, electromobility, BRT, hyperloop, shared use mobility and mobility-as-a-service shape transport futures for

the context of smart cities?," Urban Sci., vol. 1, no. 36, pp. 1–21, 2017.

[147] T. D. Chen, K. M. Kockelman, and J. P. Hanna, "Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions," Transp. Res. Part A Policy Pract., vol. 94, pp. 243–254, 2016.

[148] R. MCCAULEY, "Why autonomous and electric vehicles are inextricably linked," Goverment Tecnhology, 2017. [Online]. Available: http://www.govtech.com/fs/why-autonomous-and-electric-vehicles-are-inextricably-linked.html. [Accessed: 04-Sep-2018].

[149] D. Wu, Q. Liu, Y. Li, J. A. McCann, A. C. Regan, and N. Venkatasubramanian, "Adaptive lookup of open wifi using crowdsensing," IEEE/ACM Trans. Netw., vol. 24, no. 6, pp. 3634–3647, 2016.

[150] V.-D. Doan, H. Fujimoto, T. Koseki, T. Yasuda, H. Kishi, and T. Fujita, "Simultaneous optimization of speed profile and allocation of wireless power transfer system for autonomous driving electric vehicles," IEEJ J. Ind. Appl., vol. 7, no. 2, pp. 189–201, 2018.

[151] D. Wu, D. I. Arkhipov, M. Kim, C. L. Talcott, A. C. Regan, J. A. McCann, and N. Venkatasubramanian, "ADDSEN: Adaptive data processing and dissemination for drone swarms in urban sensing," IEEE Trans. Comput., vol. 66, no. 2, pp. 183–198, 2017.

[152] Z. Yi, J. Smart, and M. Shirk, "Energy impact evaluation for eco-routing and charging of autonomous electric vehicle fleet: Ambient temperature consideration," Transp. Res. Part C Emerg. Technol., vol. 89, pp. 344–363, 2018.

[153] A. Y. S. Lam, J. J. Q. Yu, Y. Hou, and V. O. K. Li, "Coordinated autonomous vehicle parking for vehicle-to-grid services: Formulation and distributed algorithm," IEEE Trans. Smart Grid, vol. 9, no. 5, pp. 4356–4366, 2018.

[154] D. J. Fagnant and K. Kockelman, "Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations," Transp. Res. Part A Policy Pract., vol. 77, pp. 167–181, 2015.

[155] "Nord Pool," Spot day-ahead electricity market. [Online]. Available: http://www.nordpoolspot.com/Market-data1/Elspot/Area-Prices/DK/Hourly/?view=table. [Accessed: 28-Jul-2017].

Nataly Bañol Arias received the B.Sc. degree in Production Engineering from the Universidad Tecnológica de Pereira, Colombia in 2012 and the M.Sc. degree in Electrical Engineering from the Universidade Estadual Paulista "Julio de Mesquita Filho (UNESP), Ilha Solteira, Brazil, in 2015. She is currently pursuing the Ph.D. degree in Electrical Engineering at UNESP, Ilha Solteira, Brazil. Her areas of research are the development of methodologies for the optimization, planning, and control of electrical power systems.

Seyedmostafa Hashemi (S'09, M'16) received the B.Sc. and M.Sc. degree (first class hons.) from Isfahan University of Technology, Isfahan, Iran, in 2006 and 2009, respectively, and the PhD degree from the Technical University of Denmark in 2015, all in electric power engineering. Since 2015, he has been a Postdoc at the Center for Electric Power and Energy, Technical University of Denmark. His research interests include battery and EV services in distribution systems, and grid integration of renewable energy sources.

Peter Bach Andersen, PhD, works as senior scientific researcher at the Centre for Electric Power and Energy, part of the Technical University of Denmark. His main area of research is on how grid integrated electric vehicles may support a stable, economic power system based on renewable energy. He has acted as principle investigator in two national projects – currently the Parker project in collaboration with vehicle manufacturers.

Chresten Træholt received the M.Sc. degree in electrical engineering in 1987 and the Ph.D. degree in materials science in 1994, both from the Technical University of Denmark, Lyngby, Denmark. He worked as research scientist at the Technical University Delft, the Netherlands as well as several years of experience with the superconductor cable industry. He is currently associated professor at the Center for Electric Power and Energy, Department of Electrical Engineering, Technical University of Denmark. His current fields of interest include smart grids, renewable energy, electric vehicles and superconductivity.

Rubén Romero (M'93–SM'08) received the B.Sc. and P.E. degrees from the National University of Engineering, Lima, Perú, in 1978 and 1984, respectively, and the M.Sc. and Ph.D. degrees from the Universidade Estadual de Campinas, Campinas, Brazil, in 1990 and 1993, respectively. He is currently associated Professor of electrical engineering with the Universidade Estadual Paulista "Julio de Mesquita Filho," Ilha Solteira, Brazil. His research interests include methodologies for the optimization, planning, and control of electrical power systems; applications of artificial intelligence in power system.

E3. Assessment of Economic Benefits for EV Owners Participating in the Primary Frequency Regulation Markets

Nataly Bañol Arias, Seyedmostafa Hashemi, Peter Bach Andersen, Chresten Træholt, and Rubén Romero,

Nataly Bañol Arias and Rubén Romero are with the UNESP – Sao Paulo State University, School of Engineering of Ilha Solteira, Electrical Engineering Department, Ilha Solteira, São Paulo, Brazil.

Seyedmostafa Hashemi[1], Chresten Træholt and Peter Bach Andersen are with the Center for Electric Power and Energy, Technical University of Denmark, Kongens Lyngby, Denmark.

***Abstract* — Transportation electrification plays an important role in developing more sustainable systems. As a result, the adoption of electric vehicles (EVs) is increasingly endorsed by governmental policies. It can be more strongly encouraged through the provision of different ancillary services using vehicle-to-grid (V2G) enabled EVs. This paper presents an assessment of the economic benefits of using EVs to participate in the primary frequency regulation markets. A simulation-based approach is used to evaluate a set of operation strategies, and a comparison analysis is performed using four EVs with different battery capacities providing frequency-controlled normal operation reserves (FCR-N) in the Nord Pool market. The assessment of the optimal bids is performed considering the influence of the operation strategies and the customer preferences. In addition, the effect of FCR-N on EV battery degradation and the grid impact caused by the service provision are considered in the economic evaluation. The results estimate annual benefits ranging between €200 and €2000 per vehicle, which demonstrates that EV owners can obtain substantial revenues by providing FCR-N.**

***Index Terms*—Battery degradation, Economic assessment, Electric vehicles, Frequency regulation, Operation strategies, V2G services.**

[1] Corresponding author: Seyedmostafa Hashemi
Postal address: Technical University of Denmark
Elektrovej, Building 325, room 162
2800 Kgs. Lyngby
Ph: +45 45 25 56 53
Email: shtog@elektro.dtu.dk
This paper has not been presented at any conference or submitted elsewhere previously.