Autonomous Demand Side Management of Electric Vehicles

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UiA University of Agder

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Doctoral Dissertation for the Degree *Philosophiae Doctor (Ph.D.)*
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Dedicated to
my parents
M.A.Ranathunga and Malani Swarnathilaka
my husband
Buddhi Madusanka
and my sister
Hasanthika Koshali

Preface

This thesis is submitted in partial fulfillment of the requirements for the Ph.D. degree at the University of Agder (UiA). The research work was conducted during the period from August 2018 to May 2022 at the Department of Engineering and Science, Renewable Energy section. Part of this thesis has been funded by the Christian Doppler Research Association (CDG), during my employment at the Josef-Ressel Center for Applied Scientific Computing in Energy, Finance, and Logistics. The financial support by the Austrian Federal Ministry of Science, Research and Economy and the National Foundation for Research, Technology, and Development are gratefully acknowledged.

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With deep love and affection, I express my sincere gratitude to my parents and my sister who always stood behind me and cheered me through all these years. Last but not least, my heartfelt thanks go to my husband, for his deep understanding, love, and support given to me. He shared all the ups and downs with me all these years and encouraged me throughout this venture.

M.A.S.T. Ireshika
Bregenz
28.12.2022

Abstract

Demand-side management approaches that exploit the temporal flexibility of electric vehicles have attracted much attention in recent years due to the increasing market penetration. These demand-side management measures contribute to alleviating the burden on the power system, especially in distribution grids where bottlenecks are more prevalent. Electric vehicles can be defined as an attractive asset for distribution system operators, which have the potential to provide grid services if properly managed. In this thesis, first, a systematic investigation is conducted for two typically employed demand-side management methods reported in the literature: A voltage droop control-based approach and a market-driven approach. Then a control scheme of decentralized autonomous demand side management for electric vehicle charging scheduling which relies on a unidirectionally communicated grid-induced signal is proposed.

In all the topics considered, the implications on the distribution grid operation are evaluated using a set of time series load flow simulations performed for representative Austrian distribution grids.

Droop control mechanisms are discussed for electric vehicle charging control which requires no communication. The method provides an economically viable solution at all penetrations if electric vehicles charge at low nominal power rates. However, with the current market trends in residential charging equipment especially in the European context where most of the charging equipment is designed for 11 kW charging, the technical feasibility of the method, in the long run, is debatable.

As electricity demand strongly correlates with energy prices, a linear optimization algorithm is proposed to minimize charging costs, which uses next-day market prices as the grid-induced incentive function under the assumption of perfect user predictions. The constraints on the state of charge guarantee the energy required for driving is delivered without failure. An average energy cost saving of 30% is realized at all penetrations. Nevertheless, the avalanche effect due to simultaneous charging during low price periods introduces new power peaks exceeding those of uncontrolled charging. This obstructs the grid-friendly integration of electric vehicles.

The decentralized control framework proposed in the thesis to overcome the prob-

lems of a price-driven approach employs a power signal as the grid-induced incentive function. It demonstrates compelling results in achieving valley filling in the demand curve compared to its centralized counterpart at all penetrations. The linear approximation to the non-linear optimization problem definition reduced the runtime by a factor of 32 at a penetration of 40% as a result of the computational load being distributed across all the electric vehicle controllers. Contrary to the centralized implementation, the approach proposed even at full penetration (i.e. 100%) does not exhibit scalability issues. For the conceptual validation, in addition to the perfect predictions of users' mobility behavior, a charging characteristic with a variable charge rate is assumed. Furthermore, a perfectly-forecasted aggregate demand profile and aggregate electric vehicle demand are also assumed.

The linear formulation is extended to a mixed integer linear formulation that incorporates a semi-continuous charging characteristic to comply with the charging standards defined by IEC 61851. This formulation demonstrates a risk of forming inferior peaks in the demand curve, caused by the more restricted flexibility imposed by the limitation of the minimum charging currents. A grouping and a randomization mechanism are proposed to overcome this drawback. The method yields comparable results to the linear formulation.

To facilitate the feasibility of the proposed method in practical environments, a framework driven by model predictive control is proposed in order to minimize the impact of the estimation errors associated with the different uncertainties (electric vehicle usage, and non-electric vehicle demand). The predictions are made using state-of-the-art methods. A long short-term memory recurrent neural network is used for day-ahead demand profile predictions. A k-nearest neighbors algorithm is used to estimate the mobility profiles of electric vehicle users based on historical data. The MPC-based method shows comparatively robust performance against the uncertainty in demand. The uncertainty in the mobility profile estimations exerts a greater impact on the performance. Although the proposed MPC-driven method under these uncertainties does not reach the ideal solution, it demonstrates significant potential in achieving the valley filling objective reducing the variance of demand by a factor of 4.8 in comparison to the uncontrolled scenario when both considered uncertainties are present. Hence, the method serves as a practically feasible, economical method for distribution system operators to ensure a grid-friendly integration of electric vehicle loads.

Sammendrag

Tilnærminger til styring på etterspørselssiden som utnytter den tidsmessige fleksibiliteten til elektriske kjøretøy har fått mye oppmerksomhet de siste årene på grunn av den økende markedspenetrasjonen. Disse tiltakene for etterspørselsstyring bidrar til å redusere belastningen på kraftsystemet, særlig i distribusjonsnett der flaskehalser er mer utbredt. Derfor kan elbiler defineres som en attraktiv ressurs for nettselskapene, som har potensial til å levere nettjenester hvis de forvaltes på riktig måte. I denne avhandlingen gjennomføres først en systematisk undersøkelse av to typiske metoder for styring av etterspørselssiden som er rapportert i litteraturen: en tilnærming basert på kontroll av spenningsfall, og en markedsdrevet tilnærming. Deretter er et kontrollskjema foreslått for desentralisert, autonom styring av etterspørselssiden for planlegging av lading av elektriske kjøretøy som er avhengige av et ensrettet kommunisert nettindusert signal.

For å evaluere implikasjonene for driften av distribusjonsnett, som følge av algoritmene på etterspørselssiden, ble et sett med tidsserier av lastflytsimuleringer utførte innenfor rammen av representative østerrikske distribusjonsnett.

Droop-kontrollmekanismer blir diskuterte for ladestyring av elektriske kjøretøy som ikke krever kommunikasjon. Metoden gir en økonomisk levedyktig løsning ved alle penetrasjoner hvis elektriske kjøretøy lades ved lave nominelle effekthastigheter. Men, med dagens markedstrender for ladeutstyr for boliger, særlig i europeisk sammenheng, der det meste av ladeutstyret er konstruert for 11 kW lading, er metodens tekniske gjennomførbarhet åpen for debatt.

Ettersom elektrisitetsetterspørselen er i sterk korrelasjon med energiprisene, en lineær optimaliseringsalgoritme for å minimere ladekostnadene er foreslått, som bruker morgendagens markedspris som den nettinduserte insentivfunksjonen under forutsetning av perfekte prognoser fra forbrukerne. Begrensningene på ladetilstanden garanterer at energien som kreves for kjøring, leveres uten svikt. En gjennomsnittlig energikostnadsbesparelse på 30% ble realiserte ved alle gjennomføringer. Likevel, lavineffekten introduseres på grunn av lading samtidig i lavprisperioder fører til nye og flere effekttopper enn ved ukontrollerte lading. Dette hindrer en nettvennlig integrering av elektriske kjøretøy.

Det desentraliserte kontrollrammeverket som foreslås i avhandlingen for å overvinne

problemene med en prisdrevet tilnærming, benytter et effektsignal som nettindusert insentivfunksjon. Det viser overbevisende resultater når det gjelder å oppnå dalfylling i etterspørselskurven sammenlignet med det sentraliserte ved alle penetrasjoner. Den lineære tilnærmingen til den ikke-lineære optimaliseringsproblem reduserte kjøretiden med en faktor på 32 ved en penetrasjon på 40% som resultat av at beregningsbelastningen ble fordelt på alle elbilkontrollerne. I motsetning til den sentraliserte implementeringen viser ikke den foreslåtte tilnærmingen skalerbarhetsproblemer selv ved full penetrasjon (dvs. 100%). For den konseptuelle valideringen antas det, i tillegg til perfekte prediksjoner av brukernes mobilitetsatferd, en ladekarakteristikk med variabel ladehastighet. Videre ble det også forutsatt en perfekt prognostisert og aggregert etterspørselsprofil og aggregert etterspørsel etter elbiler.

Den lineære formuleringen er utvidet til et blandet heltall lineær formulering som inneholder en semi-kontinuerlig ladekarakteristikk for å overholde ladestandardene definert av IEC 61851. Denne formuleringen viser en risiko for å danne dårligere topper i etterspørselskurven, forårsaket av den mer begrensede fleksibiliteten som pålegges av begrensningen av minimum ladestrømmer. En gruppering og en randomiseringsmekanisme er foreslått for å overvinne denne ulempen. Metoden gir sammenlignbare resultater med den lineære formuleringen.

For å lette gjennomførbarheten av den foreslåtte metoden i praktiske miljøer, foreslås et rammeverk drevet av modellprediktiv kontroll for å minimere virkningen av estimeringsfeil knyttet til de ulike usikkerhetene (bruk av elektriske kjøretøy og etterspørsel etter ikke-elektriske kjøretøy). Prognoser ble gjort ved hjelp av toppmoderne metoder. Et tilbakevendende nevralt nettverk med lang korttidshukommelse ble brukt til å forutsi etterspørselsprofilen dagen i forveien. En k-nærmeste naboeralgoritme ble brukt til å estimere mobilitetsprofilene til elbilbrukere basert på historiske data. Den MPC-baserte metoden viser forholdsvis robust ytelse i forhold til usikkerheten i etterspørselen. Usikkerheten i estimatene av mobilitetsprofilene har større innvirkning på resultatene. Selv om den foreslåtte MPC-drevne metoden under disse usikkerhetene ikke når den ideelle løsningen, viser den et betydelig potensial for å nå målet om å fylle dalen ved å redusere variansen i etterspørselen med fem ganger sammenlignet med det ukontrollerte scenariet når begge de vurderte usikkerhetene er til stede. Metoden fungerer derfor som en praktisk gjennomførbar, økonomisk metode for distribusjonssystemoperatører for å sikre en nettvennlig integrering av elbilbelastninger.

Publications

In the following, the publications related to the research conducted in the Ph.D. are presented. Publications A-E are reproduced as Part II of this dissertation. Publications F-H which are listed as the second part of this list are not included in this dissertation. While the five included papers are sorted according to the topics studied in this dissertation, the other two papers are sorted in chronological order according to the dates of their publication.

Publications Included in the Dissertation

- **Paper A:** Ireshika, Muhandiram Arachchige Subodha Tharangi, Markus Preissinger, and Peter Kepplinger. "Autonomous demand side management of electric vehicles in a distribution grid." In 2019 7th International Youth Conference on Energy (IYCE), pp. 1-6. IEEE, 2019.

- **Paper B:** Ireshika, Muhandiram Arachchige Subodha Tharangi, Ruben Lliuyacc-Blas, and Peter Kepplinger. "Voltage-Based Droop Control of Electric Vehicles in Distribution Grids under Different Charging Power Levels." Energies 14, no. 13: 3905, 2021.

- **Paper C:** Ireshika, Muhandiram Arachchige Subodha Tharangi, Klaus Rheinberger, Ruben Lliuyacc-Blas, Mohan Lal Kolhe, Markus Preißinger, and Peter Kepplinger. "Optimal power tracking for autonomous demand side management of electric vehicles." Journal of Energy Storage 52: 104917, 2022.

- **Paper D:** Ireshika, M.A.S.T., and Kepplinger, P., "IEC 61851 Compliant Demand Side Management Algorithm for Electric Vehicle Charging: A MILP Based Decentralized Approach." The 13th Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MEDPOWER 2022), IET, 2022 (accepted, in press).

- **Paper E:** Ireshika, M.A.S.T., and Kepplinger, P., "Uncertainties in model predictive control for decentralized autonomous demand side management of electric vehicles.", Submitted to Applied Energy, Dec 2022 (Manuscript No: APEN-D-22-12873).

Other Publications Not Included in the Dissertation

- **Paper F:** Kepplinger, Peter, Bernhard Fässler, Gerhard Huber, Muhandiram Arachchige Subodha Tharangi Ireshika, Klaus Rheinberger, and Markus Preißinger. "Autonomes Demand Side Management verteilter Energiespeicher." e & i Elektrotechnik und Informationstechnik 137, no. 1: 52-58, 2020.

- **Paper G:** Arachchige ST, Schober L, Lliuyacc R, Kepplinger P, Preissinger M. "Voltage-Based Autonomous Demand Side Management of Electric Vehicles." In Tagungsband des 12. Forschungsforum der österreichischen Fachhochschulen (FFH) 2020; FH Wien, Wien, Austria, 2020.

- **Paper H:** Lliuyacc-Blas, Ruben, Svein Olav Nyberg, Muhandiram Arachchige Subodha Tharangi Ireshika, Mohan Lal Kolhe, and Peter Kepplinger. "PV Hosting Capacity Estimation in Low Voltage Feeders Through Bayesian Statistical Inference." In 2022 12th International Conference on Power, Energy and Electrical Engineering (CPEEE), pp. 250-255. IEEE, 2022.

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PART I

Chapter 1

Introduction

The global electric vehicle (EV) fleet expanded significantly over the last few years. According to IEA reports, electric car registrations increased by 41% in 2020, despite the pandemic-related worldwide downturn in car sales in which global car sales dropped by 16% [1, 2]. Nearly 10% of global car sales were electric in 2021. The International Energy Agency (IEA's) latest statistics for EV uptake from 2010 to 2021 are presented in Figure 1.1. According to these records, electric car sales have kept rising with 2 million cars sold in the first quarter even in the year 2022. The strong momentum in the electric car market is predominantly attributed to supportive regulatory frameworks to strengthen key policies like zero-emission vehicle mandates, fiscal subsidies for EVs, expansion in the economic battery technology, and interest toward fossil fuel autonomy.

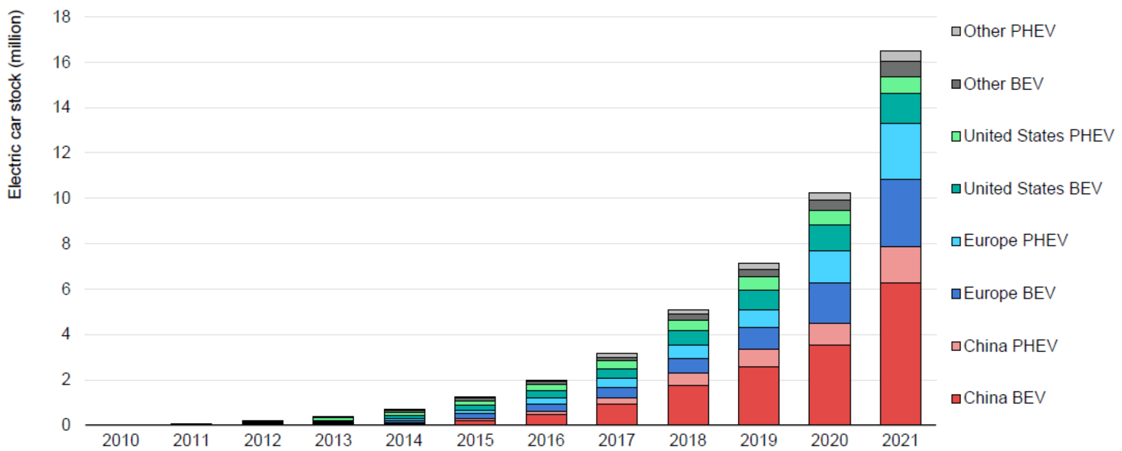

Figure 1.1: Global electric car stock, 2010-2021 [2]

Electrification of the transport sector offers opportunities to reduce direct dependency on fossil fuels, reduce carbon emissions, and improve local air quality. Although the EV adaptation builds new connections between the transportation and electric sectors, it poses numerous operational challenges to the electricity network both at bulk and distribution levels. A vast body of research has investigated the impacts of uncontrolled EV charging on the existing power system. The bulk power system is designed with greater resilience to demand growth thus expected to be able to withstand the widespread EV adaptation. However, the distribution systems where the EVs customarily interact, encounter far greater challenges with this transition. Clustering effects in EV charging loads at the local level might lead to high EV concentrations even if overall adoption remains low, triggering extreme surges in demand at peak hours [3]. Furthermore, it can lead to undesirable voltage deviations, high power losses, and asset overloading (cables and transformer) risking the stability and security of the power grid [4, 5, 6, 7, 8]. Such effects can be exacerbated when higher in-home power charging is employed [3].

The aforementioned challenges could be overcome by reinforcing the grid assets. The high investment costs and the installation duration of the associated reinforcements, however, represent a trade-off. Although increasing network flexibility through supply-side options was the main focus in the past, recent transformations in the network architecture have opened up alternative possibilities. As opposed to the traditional approach of matching supply to demand, in certain cases, it is more efficient to have demand match supply which is termed demand side management (DSM) [9].

DSM is a field that emerged in the late 1970s and exploits demand flexibility through the engagement of active consumers. It is defined as the planning and implementation of those electric utility activities designed to influence customer uses of electricity in ways that will produce desired changes in the utility's load shape [10]. Three concepts are distinctly identified in DSM: energy efficiency (EE), energy conservation (EC), and demand response (DR). The definition of the DR includes all intentional modifications to consumption patterns of electricity of end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption. These DSM measures are gaining increasing attention in light of the increased complexity added to the electric power systems, due to a growing number of distributed generators and variable renewable sources being integrated into the system. Furthermore, the integration of information and communication technologies, automation, and control in the smart grids through advanced metering infrastructure, sensors, and digital network management devices enable the exploitation of efficient DSM strategies.

EV loads are regarded as flexible loads exhibiting a high potential for temporal flexibility. Analysis of the 2017 National Household Travel survey data shows that personal light-duty vehicles in the US are parked on average 95.8% of the time which indicates the suitability of EV loads for DSM [11]. This temporal flexibility, in combination with the large storage capacity of the EV batteries, renders them an ideal candidate for DSM services. With properly designed DSM schemes, EV loads can be utilized to provide different grid services either through managed charging or power transfer to the grid. Although grid integration of EVs is challenging, the high flexibility of EVs offers unique opportunities to complement electricity grid operations. Furthermore, the demand-side flexibility resulting from the controlled EV charging offers a potentially cost-effective alternative to conventional grid reinforcements.

Numerous DSM strategies are discussed in the literature to exploit the flexibility of EVs. In recent years, managed charging programs have grown in number, program size, sophistication, and diversity in approach, and gained a high momentum. The manifested diversities are reflected in the respective objectives, associated algorithms, and approaches, required resources, associated costs, etc. However, the primary goal of all these strategies is to regulate charging power and/or shift the EV charging in time without disrupting the mobility requirements.

Managed charging of EVs can be achieved with either passive or active control mechanisms. Moreover, it can be designed with unidirectional (V1G) or bidirectional (V2B, V2G, or V2X) power flow as required. The order of complexity, communication requirements and resource requirements differs among these different methods. The following section summarizes the state of the art pertaining to EV-controlled charging featuring diverse approaches and resource requirements.

Passive managed charging: Also known as behavioral load control, passive managed charging is driven by customer behavior. EV customers respond to a signal with the intention to change their charging behavior, which can be done either manually or automatically (with automatic timers)[12, 9]. Passive load control can be realized with Time-of-use (TOU) or real-time pricing (RTP) which are relatively easy to deploy on account of their lower complexity and reduced communication requirements. However, charging management achieved through passive load control is uncoordinated, thus the anticipated favorable impacts on grid operations may not be realized. This type of uncoordinated charging when adopted largely can eliminate the smoothing effect due to the natural stochastic features of EV charging demand, forcing demand synchronization among all the consumers. If not properly designed, it could lead to an unfavorable new rebounding peak during the low-price periods, especially at high EV integration [13, 14].

Actively managed charging: Given the limitations associated with passive load control, active management strategies for EV charging are being developed to provide more efficient solutions to meet the challenges of the grid. Emerging technologies in electricity grids equipped with smart features permit the deployment of active managed charging. In this approach, EVs respond directly to a control signal originating from the utility or an aggregator [12, 9]. The degree of complexity of the control method varies depending on the implementation. Two strategies for active charging management are available: 1) centralized and 2) decentralized controls.

Centralized charging: The main concept underlying the centralized charging approach is to utilize its centralized framework to acquire the information from the EVs and provide a globally optimal solution considering all the grid and user constraints. In this approach, a master control engine performs the decision-making concerning the charging rate and schedule of the grid-connected EVs. A diverse range of algorithms has been investigated in the literature to achieve centralized charge control, covering a diverse portfolio of objectives as summarized in Table 1.1. The table also provides more details on the power flow mode, consideration of user preferences, and provisions to facilitate ancillary services such as frequency regulation and voltage regulation.

Table 1.1: An overview of the literature on centralized charging control.

Ref.	V2G	Objective	Method	EV owner preference	Ancillary services
Deilami, Sara, et al.[15]	✗	minimization of active power losses and improve voltage profile	maximum sensitivity selection optimization	✓	
Khatiri-Doost, S., et al.[16]	✓	minimization of distribution system demand and minimization of active power losses	priority based optimization	✓	
Masoum, Amir S., et al.[17]	✗	minimization of distribution system demand and minimization of active power losses	maximum sensitivity selection optimization	✓	
Han, S., et al.[18]	✓	frequency regulation	dynamic programming		✓
Lopes, J. A. P., et al.[19]	✗	improving voltage profile and line congestion	heuristics	✗	✗
Singh, M., et al.[20]	✓	peak power management and voltage stability	fuzzy logic	✗	✓
Galus, M. D., et al.[21]	✓	minimizing the charging cost	agent based optimization	✗	✓
Singh, M., et al.[22]	✓	minimization of distribution system demand and minimization of active power losses	heuristics	✗	✓
Xu, Zhiwei, et al.[23]	✗	minimization of distribution system demand and minimization of active power losses	quadratic, convex, heuristics	✗	✗

The centralized approach demands a sophisticated communication infrastructure for network management and back-end services, which adds complexity and costs to the system. In addition, it suffers from heavy computational costs and experiences challenges in scalability due to the increased dimensionality specifically at high EV market penetrations. For this reason, research studies employing centralized approaches are usually limited to studies with small sizes of EV fleets. Furthermore, the centralized method faces challenges related to data security and privacy.

Decentralized charging: The decentralized approach makes the charging decisions locally at each EV in response to a signal received from the grid side, whereby the computational burden is distributed among the participating EVs. Hence, it demands a certain degree of computational intelligence on the side of the EV customer. The reduced computational complexity resulting from the distributed nature underpins the scalability at high penetrations. However, the method does not provide a guarantee of a globally optimal solution with EVs establishing their charging schedule without coordination with other EVs. An overview of the literature on

Table 1.2: An overview of the literature on decentralized charging control.

Ref.	V2G	Objective	Method	Communication
Ma, Z., et al.[24]	✗	Minimize individual charging cost and distribution system peak demand	game theory	bidirectional
Chen, N., et al.[25]	✗	Minimize individual charging cost and distribution system peak demand	nested optimization	bidirectional
Gan, L., et al.[26]	✗	Minimize individual charging cost and distribution system peak demand	iterative negotiation algorithm	bidirectional
Li, Q., Cui, T., et al.[27]	✗	Minimize the distribution system load variance	myopic algorithm	bidirectional
Rotering, N., et al.[28]	✓	Maximize the profits of EV consumers	dynamic programming	unidirectional
Cao, Yijia, et al.[29]	✗	Minimize the charging cost	heuristics	unidirectional
Vaya, M. G., et al.[30]	✗	Minimizes charging costs and distribution system peak demand	genetic algorithm	unidirectional

EV management using the decentralized approach is presented in Table 1.2, also indicating the power flow mode, the communication requirement, and the objective of the optimization. The decentralized method has gained much attention in the field of research related to DSM due to the reduced computational cost, reduced communication resource requirements, enhanced data privacy, and security, etc. As discussed in the previous sections, a multitude of approaches to charging management has been proposed in the literature, demonstrating a substantial potential to reach the goals of DSM. These approaches require different scales of resources and enablement costs. The majority of the works being suggested in the literature require bi-directional communication, thus the economic feasibility is open to question due to the associated costs for the communication infrastructure. Only a few instances of DSM strategies with unidirectional communication are proposed in the literature. However, these studies neglect some important design aspects that are crucial for practical deployments, such as the incorporation of associated uncertainties (EV-related uncertainty, non-elastic demand uncertainties, etc) and compliance with the charging standards.

The aim of the work presented in this thesis is therefore to develop a DSM solution for EV management which is both technically, economically, and practically feasible. To reach this goal, a method that requires less communication, less computational cost, and is easy to integrate into the existing charging infrastructure is being sought.

1.1 Contributions

In order to achieve the above objective, the following contributions were made within the framework of this doctoral thesis.

- A set of systematic studies are performed to assess the impact of EV charging impacts on the operation of the distribution grids under different EV market penetrations using time series load flow simulations in contrast to classical snapshot load flow simulation. Several DSM strategies with different levels of resources are tested and the resulting impact on grid operation is evaluated.

- The feasibility of a communication-free DSM strategy for residential EV charging which has been proposed in the literature is investigated. A systematic analysis of the proposed methodology is performed focusing on all existing residential charging power rates and a full range of EV penetrations to gain a broader outlook.

- A conceptual framework of a decentral ADSM strategy for EV scheduling is designed where the communication requirement is strictly unidirectional.

- A novel two-layered decentralized ADSM strategy based on the developed conceptual framework is implemented. The fundamental principle of the method is to track a reference power signal and is therefore referred to as Optimal Power Tracking (OPT). The performance of the proposed method is evaluated and compared with its centralized counterpart.

- The proposed OPT architecture is extended to meet the charging standards defined in IEC 61851 [31] to incorporate the design aspects with respect to real-world deployment.

- To accommodate the uncertainties present within the OPT-ADSM approach, a model predictive control scheme is investigated.

The structure of the published papers highlighting the different research topics considered is illustrated in Figure 1.2.

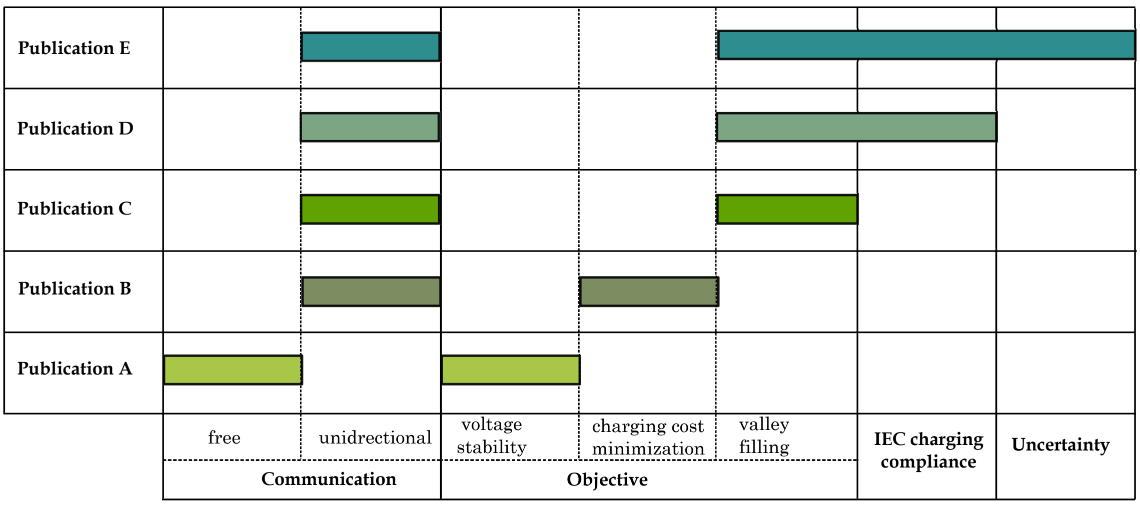

Figure 1.2: The conceptual framework of the proposed unidirectional ADSM for EV charging

1.2 Thesis Outline

The dissertation is organized into two parts. Part I contains an overview of the work carried out throughout this Ph.D. study and Part II includes a collection of five published or submitted papers, which are listed in the list of publications. In addition to the introduction chapter presented above, the following chapters are included.

- Chapter 2 presents an overview of the methods and models used in the simulation studies followed by a detailed description of the developed ADSM approach for EV charging scheduling.
- Chapter 3 presents an overview of a decentralized fully autonomous communication-free ADSM strategy and emphasizes its feasibility for typical charging residential charging power rates for a range of EV penetrations which are presented in Paper A.
- Chapter 4 presents the simulation results for the proposed control algorithm using real-time pricing as the cost function for the optimization summarizing the work in Paper B.
- Chapter 5 presents a hierarchical decentralized control algorithm developed to achieve the valley filling objective by tracking a reference power signal as presented in Publication C.
- Chapter 6 includes a mixed integer linear formulation for the decentralized algorithm introduced in Chapter 5 to achieve compliance with the charging standards as discussed in Paper D.
- Chapter 7 includes a model predictive control (MPC) driven framework to incorporate the associated uncertainties. This chapter outlines Paper E.
- Chapter 8 contains the conclusion, in which the main findings are highlighted.
- Chapter 9 concludes the dissertation by highlighting a few potential future research directions relevant to the topic addressed in this dissertation.

Chapter 2

Simulation Models and Methods

In order to perform a systematic analysis of all the DSM strategies proposed in this study, a set of load flow simulations of a distribution grid model is used. The outcomes of the model are used to evaluate and build a more comprehensive portrait of the grid status. Unlike the simplified methods used in most studies, which either use superposition or focus on single EV use cases, this work uses the analytical results from the power flow simulation (voltages at each node, currents in each cable, total load at the transformer, etc.) in the evaluations. This chapter underlines a detailed description of the in-house grid simulation tool [32] used to perform the load flow calculations.

2.1 Grid Simulation Tool

The grid simulation tool developed is an integration of different network elements as presented in Figure 2.1. This tool was developed in Matlab to provide a platform for evaluating time series power flow studies. Additionally, it features an interface for testing and evaluating DSM strategies for various flexible devices such as EVs, stationary battery systems [33], heat pumps, photovoltaics, etc. This also can be used for short-circuit fault analysis studies. Each of the modules in the presented tool is described in detail in the following section.

2.1.1 Grid Model

The load-impedance matrix is an elementary component in the power flow calculations. The grid model element in Figure 2.1 is used to build up this impedance matrix and to represent the topological characteristics of the grid. The essential information for the grid modeling includes the network topology, cable and overhead line parameters (types and lengths), cable and overhead library data (per unit impedance, ampere ratings, etc), transformer parameters, consumer-related data (type, number, and locations, annual energy consumption) of the grid. In this study, the simulations are carried out using the information on selected representative low-voltage (LV) grids in Austria in which all the necessary model parameters and the

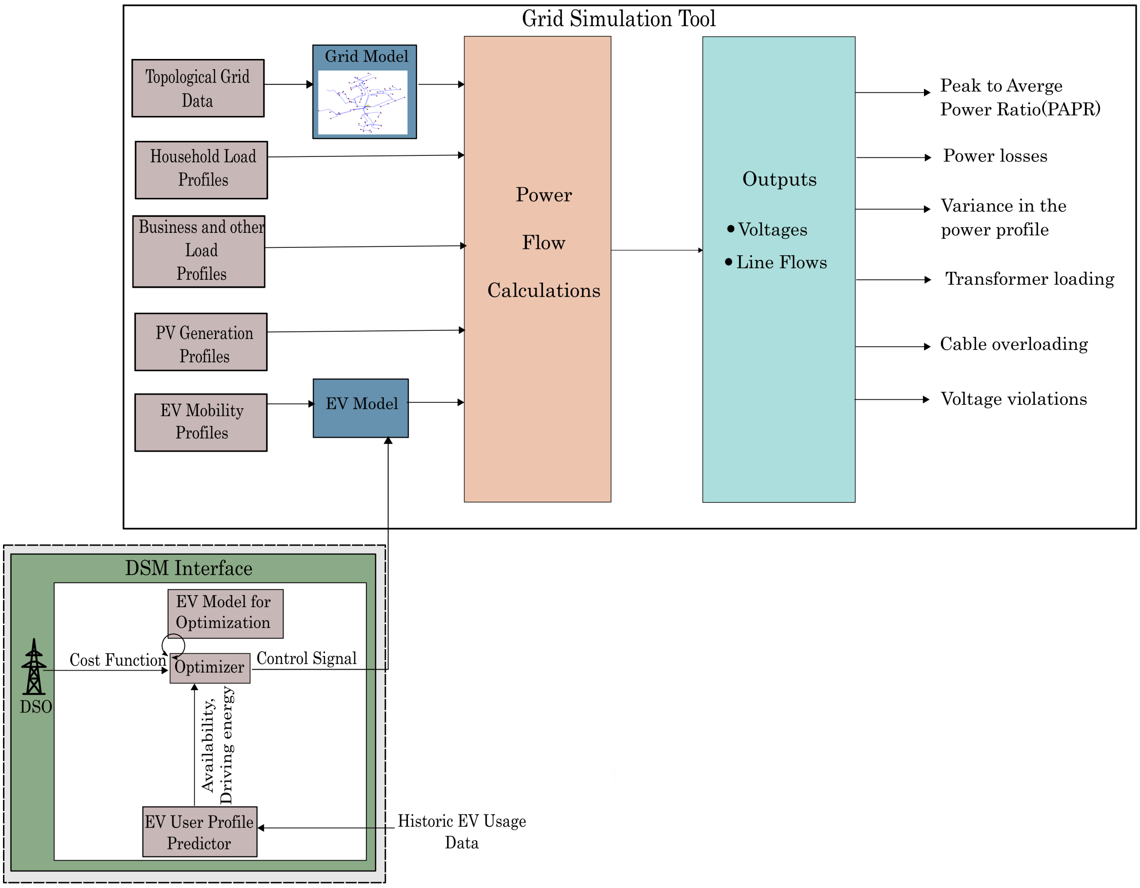

Figure 2.1: Grid simulation model

load information were available. Therefore, more realistic use cases are considered to provide a representation of the European context.

2.1.2 Non-elastic Load Models

Non-elastic loads are classified into two main categories. The household loads and non-household loads such as small-scale industrial enterprises, office buildings, and commercial enterprises. Real measurements from smart meter pilot projects are used to model household loads. Consumers' annual energy consumption data from the grid model are used as mapping criteria to assign the smart meter profiles to the household load profiles. For the non-household loads, the standard load profiles of the Austrian clearing and settlement agency [34] are used. These standard profiles are scaled according to the annual energy consumption of the respective consumer unit.

2.1.3 EV Model

A simplified linear model is used to characterize the system dynamics of the EV battery as proposed in the majority of the literature on DSM of EVs. Accordingly, the energy content of the EV battery at time t, $E(t)$ is mathematically expressed by,

$$E(t) = E(t-1) \ + \eta_{\mathrm{c}} \, P^{(\mathrm{c})}(t)\Delta t \ - P^{(\mathrm{d})}(t)\Delta t, \tag{2.1}$$

where $E(t)$ is the time-dependent energy content of the battery, $P^{(\mathrm{c})}(t)$ is the charging power and $P^{(\mathrm{d})}(t)$ is the discharging power at time t. η_{c} is the charging efficiency of the charging equipment and Δt is the time step. The model neglects the standby losses of the battery.

The mobility profile data, which includes the energy consumption data of the vehicles and the availability times, is derived either from travel survey data or from pilot projects of electric vehicle charging records.

2.1.4 EV Penetration

The term EV penetration is defined as the percentage of consumer units with an EV relative to the number of total households in a grid. An EV penetration of 100% implies that all the consumer units are equipped with an EV. A maximum of one EV is assumed to be allowed at each unit. In the analysis, simulations are performed for a wide range of EV penetration to investigate the feasibility of the methods investigated across a broad spectrum of configurations.

2.1.5 Load Flow Calculations

The load flow computations are performed using the load flow technique proposed by Ghatak and Mukherjee [35]. It is an extension of the conventional backward forward sweep flow method where the load currents are calculated in the backward sweep and the bus voltages are calculated in the forward sweep based on the currents determined. It uses a single load current to bus voltage (LCBV) matrix to perform both the backward and forward sweeps of load flow calculation in a single step to determine the bus voltages directly from the load current injections as follows.

$$[V] = [V_{\mathrm{S}}] - [LCBV][I] \tag{2.2}$$

where V_{S} is the slack bus voltage, $[V]$ is the voltage vector comprising voltages at all the nodes and I is the current vector representing load current consumptions at the nodes. LCBV matrix mimics the topological structure of the distribution network. The LCBV matrix is used to establish a relation between the injected load currents and the bus voltages of the network which is utilized to compute the bus voltages directly from the load current injections. This method has been tested for both radial and weakly meshed grids.

2.1.6 Grid Simulation Outputs

The load flow calculation provides the voltage values at the buses and the current flows in the cables. With this information, various performance indices are evaluated that reflect the quality of the network operation. From the utilities' point of view, increasing the efficiency and cost-effectiveness of the system and improving reliability and power quality are among the most important aspects of cutting-edge electricity networks [36]. One of the means used to achieve the aforementioned goals is the flattening of the electricity demand curve. Two indices are used within this study to measure the flatness of the demand curve: 1) Peak to average power ratio (PAPR), and 2) variance. PAPR is an indicator of transformer utilization efficiency, which is defined as the ratio between peak and average power.

Voltage profiles at the load nodes are also investigated and compliance with the voltage norms defined in the EN 50160 [37] standard is analyzed. The EN 50160 standard is specifically chosen considering the European LV grid configurations in the simulation studies. This standard specifies that the 10-minute rms value of the supply voltage in LV distribution networks should not deviate from the nominal value more than 10 % for 95 % of the time within a week. Additionally, the 10-minute rms values of the supply voltage have to remain in the range of $[-15\ \%, +10\ \%]$ in any case.

The current carrying capacity defines the safe operating limits of a cable. Exceeding this limit will cause insulation failures due to overheating. Hence, cable loading defined as the percentage ratio between the current flowing through the cable and the maximum allowable current is investigated. These rated values are taken from the cable library of the grid model.

2.2 DSM Interface

The DSM interface block is a representation of the control algorithms proposed in this study for EV planning. The main attribute that is focused on designing the control architecture is the degree of simplicity in embedding it into the existing charging infrastructure and the required level of communication. Only unidirectional power flow (V1G) is assumed in the framework of this study.

Two branches of EV scheduling control architectures are considered in the context of this study. Paper A investigates a fully autonomous control algorithm that demands no communication which is detailed in chapter 3. The remaining publications employ a control architecture where communication is strictly unidirectional, which is described in the following section.

The proposed decentralized ADSM approach relies on a unidirectionally communicated, time-dependent control signal provided by a central entity, for instance, a distribution system operator (DSO). This signal or a variant of this signal is used as a cost function for the optimal scheduling problem of EVs. A schematic representation of the ADSM approach proposed for EV scheduling is presented in Figure 2.2.

An embedded controller integrated into the electric vehicle supply equipment (EVSE) executes an optimization routine to calculate the optimal charging scheduling for the EVs by minimizing a defined objective function. The control signal

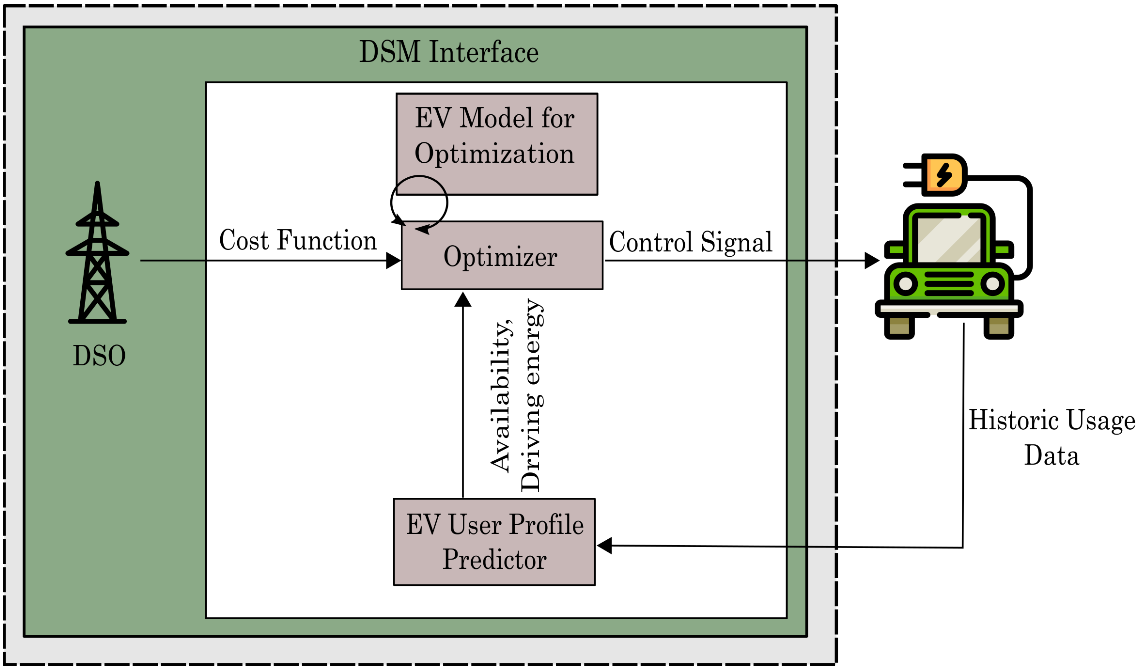

Figure 2.2: The conceptual framework of the proposed unidirectional ADSM for EV charging

defining the charging status of the EV is the decision variable in the optimization. A cost function is broadcasted by a central entity to the EVs and it serves as the incentive function in the optimization routine. The method relies on estimates of EV usage behavior, which include the energy demand for future trips together with the arrival and departure times defining the availability of the EV for charging. The historical data acquired from the EVs is fed into an EV usage profile estimator to predict each of these estimates. On the basis of these estimates and the received cost function, the optimization routine derives the control signals for EV charging using a simplified EV model by minimizing a chosen objective function. Optimization constraints are defined to guarantee the state of charge permissible limits. The linear battery model employed in the grid simulation tool is used in the optimization routine as the EV model to reduce the complexity of the problem. The proposed control function is performed locally for each grid-connected EV.

Due to the decentralized design of the proposed ADSM, it has significant advantages. The primary benefit of the proposed ADSM is the reduced communication overhead owing to the unidirectional communication requirement. Since the method is implemented as a distributed control architecture, no scalability problems arise owing to the reduced dimension of the associated optimization routines. The linear formulations adopted in the optimization routine require less computational overhead and therefore can be deployed in an embedded control system at a lower cost.

The proposed concept in the aforementioned ADSM architecture provides the basic framework for the simulation studies presented in publications B, C, D, and E. Papers B, C and D are conducted under the assumption of perfect prediction for the EV usage behavior. Paper B employs the most widely used cost function in the literature, the real-time prices (RTP), to minimize the charging cost, and discusses the resulting implications on the grid operation for a wide range of EV penetrations. A hierarchical two-layer ADSM technique using the presented framework is developed in Paper C as a part of this thesis. In the developed optimization routine, a power signal that reflects the network state is used as the cost function to achieve the valley filling objective. The method proposed in this contribution forms the basis for the studies presented in publications D and E. Publication D focuses on the compliance of the proposed method with the charging standards by adopting a mixed integer linear optimization formulation. For a more comprehensive assessment, Article E proposes an approach based on model prediction control and evaluates it, taking into account the uncertainties involved.

Chapter 3

Communication-free Autonomous Demand Side Management of EVs

With the proliferation of EV market penetration, addressing the challenges of grid integration has attracted strong research interest. Deviation from the standard voltage limits defined is one of the most common challenges with unregulated charging. Voltage-dependant charging mechanisms which only require voltage measurements at the point of connection (PCC) are discussed in the literature for mitigating voltage problems stemming from EV charging to meet the supply voltage standards such as EN 50160 [37]. However, the feasibility of this method for all currently existing residential charging power rates across all ranges of EV penetrations is an open question. In this chapter, the background of the literature on the voltage-based DSM of EV charging is presented followed by the highlights of a systematic analysis conducted on the aforementioned method which is discussed in detail in Paper A.

3.1 Voltage Droop Control

Analogous to photovoltaic (PV) converters, voltage-based controllers work on a simple droop control mechanism. The method only demands measured voltage at the connection point and adjusts the charging current reacting to the measured local voltage. The overall concept of the voltage droop control mechanism is presented in Figure 3.1. A semi-continuous characteristic is used for the charging current which is in compliance with the charging standards defined in IEC-61851 norms. Due to the simplicity of the droop controller, integration into the existing charging network is feasible with limited additional investment.

3.2 Motivation

The research studies that have been undertaken applying the voltage drop control mechanism to electric vehicle charging are summarised in Table 3.1. The existing literature fails to provide a detailed analysis of the voltage droop control mechanism for all the combinations of EV penetrations and currently available residential

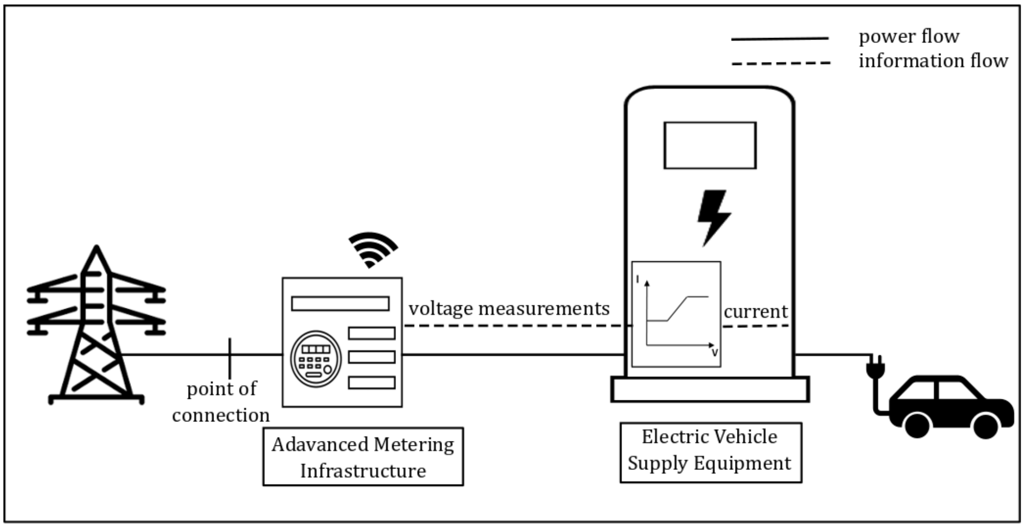

Figure 3.1: Schematics of the voltage droop control mechanism for EV charging control

charging power rates. Hence a systematic analysis is carried out and presented in Paper A, to investigate the potential of droop controlling in complying with the voltage magnitude standards in all these scenarios.

Table 3.1: An overview of the literature on voltage-based charging control and the proposed study.

Ref.	Penetration	Nominal charging power (kW)
[38]	50 %, (60 %, 70 %)	6.6
[39]	10 EVs	4
[40]	39 EVs	3.3
[41]	43 EVs	3.7
[42]	80 %	undefined
[Paper A]	**5 %, 10 % - 100 % (in steps of 10 %)**	**3.3 , 6.6 , 11**

3.3 Simulation Setup

The simulation studies are conducted assuming that each EV charging equipment is equipped with advanced metering infrastructure (AMI). This can be justified by the fact that most countries with a high penetration of EVs have set targets for the roll-out of smart meters. Three typical residential nominal charging power rates (i.e. 3.3 kW, 6.6 kW, and 11 kW) are considered in the evaluation and the results are benchmarked to the respective uncontrolled charging. Thus, in total six scenarios are investigated. U1, U2, and U3 denote the uncontrolled charging with 3.3 kW, 6.6 kW, and 11 kW nominal power rates respectively. And C1, C2, and C3 denote the droop-controlled charging for the aforementioned charging rates as stated in Paper A.

A load flow simulation of a representative LV grid in Austria is conducted using the grid simulation tool introduced in Chapter 2 over a week in the winter season with a time resolution of 15 min. The simulated LV grid comprises two 630 kVA, 10/0.42 kV step-down 3-phase transformers with 221 load nodes. The grid supplies 600 residential consumers, 52 business units, and 99 other consumer units which include heat pumps, public facilities, etc. The household load profiles are modeled using real smart meter data recorded in a field test in Austria by the local energy provider illwerke vkw AG (VKW) [43]. The commercial enterprises and other types of loads are modeled using standard load profiles of the Austrian clearing and settlement agency [34]. EV mobility profiles are generated from the records of the Austrian national mobility survey Österreich Unterwegs 2013/2014 [44]. The specifications for a Nissan Leaf electric vehicle with a battery capacity of $C_i = 24$ kWh are used. The voltage variations and compliance with the voltage standards defined in EN 50160 for LV networks at the individual nodes are analyzed.

3.4 Results

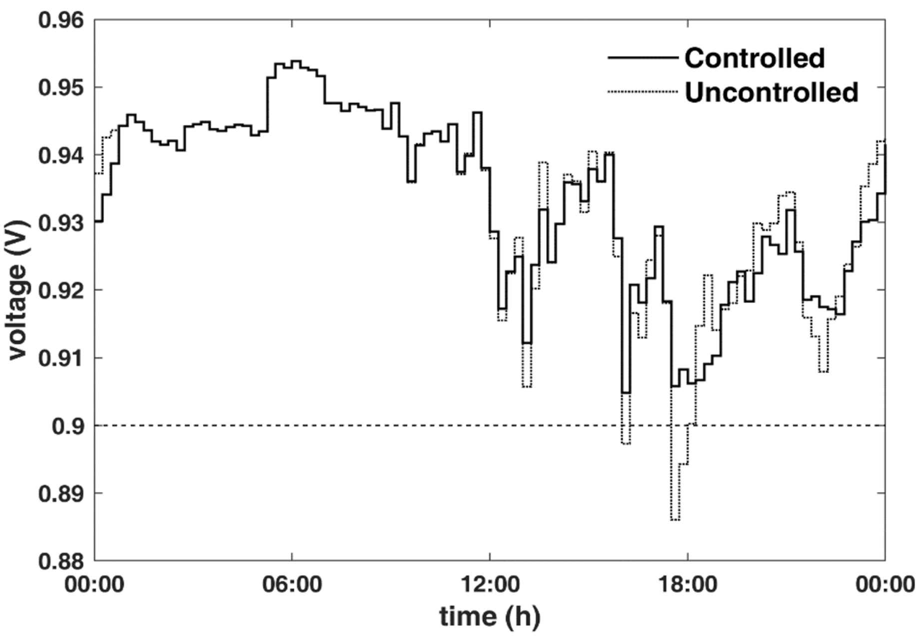

Figure 3.2: A comparison of a voltage profile of a single day at an example node

Consistent with the relevant literature, the results showed that the voltage drop control mechanism has the potential to improve the voltage profile at the grid nodes, especially during critical time intervals. Figure 3.2 presents a comparison of the voltage profile of a single day at an example node with a connected EV for both controlled and uncontrolled scenarios. The voltage profile at the node with uncontrolled charging experiences under-voltage events below the 0.9 p.u. threshold limit at some time instances, especially when the grid is operating under peak load at around 6 p.m., with most residential EVs commencing charging. Droop-controlled charging mitigates these under-voltage events stemming from uncontrolled charging and improves the overall voltage profile.

To better understand the potential of the proposed method, an in-depth analysis is carried out to assess compliance with the voltage standards for the three charging currents considered over a range of penetrations (cf. Figure 3.3). As visible in the figure, the control method successfully mitigates the voltage violations stemming from uncontrolled EV charging and ensures compliance with the voltage standards defined in ENE50160 when charged at low nominal charging power rates (i.e. 3.3 kW and 6.6 kW) at all penetrations. However, the results indicate that above 80% EV penetration, compliance with the voltage standards is not ensured by the droop controller when EV charging with a nominal power of 11 kW is employed. In addition to the grid voltage improvements, the droop controller is also capable of providing peak power reduction at the transformer by over 10% at 100% penetration. However, the users experience prolonged charging times due to the intervention of the controller. In the extreme case, at a high charging power of 11 kW and full EV penetration, a noticeable impact on the charging rate is observed where the average normalized charging reduces to 0.57.

This publication extends the findings from the existing literature to cover all the penetrations and residential charging modes available confirming the suitability of the method for early EV market penetrations. Owing to the absence of the communication requirement, the method possibly provides an economically viable solution. However, with the current market trends in residential charging equipment especially in the European context where most of the charging equipment is designed for 11 kW charging, the technical feasibility of the method, in the long run, is debatable.

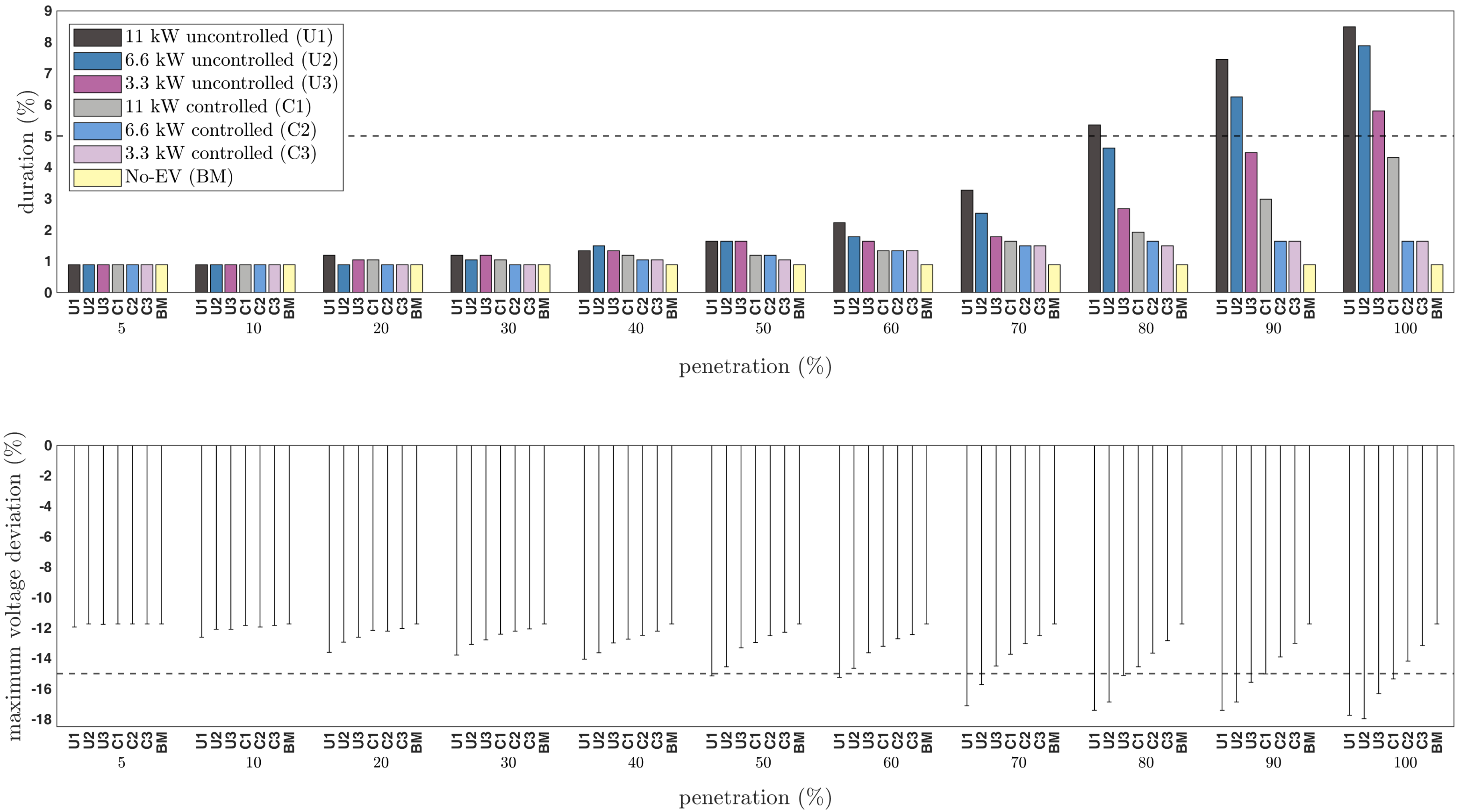

Figure 3.3: Maximum duration of the rms voltage deviation below the −10 % threshold (top), minimum voltage deviation (bottom) for the benchmark case (BM), the uncontrolled (U1-U3) and controlled (C1-C3) scenarios. The dashed lines show the threshold limits defined in the EN 50160 standard.

Chapter 4

ADSM with Market Prices

Market-based DSM programs are often discussed in the literature for EV charging scheduling in the first place where the main objective is to reduce electricity costs. In these market-based DSM programs, a dynamically changing electricity price serves as the incentive function. Following the roll-out of smart meters, time-based pricing is becoming common in the residential and commercial sectors. Consequently, market-based ADSM programs aimed at exploiting demand flexibility in the residential sector have also gained increased interest. Electricity market prices and demand are deemed to be highly correlated. As such, DSM based on market prices is considered to offer a substantial potential for exploiting demand flexibility to yield both systemic and economic benefits. In order to analyze the potential of market-driven DSM for EV flexibility management and quantify the systemic impact on distribution networks and economic gains, Publication B uses the ADSM framework proposed in Chapter 2 with real-time prices as the incentive function followed by a load flow simulation.

4.1 Method and Simulation Framework

The charging cost minimization problem in publication B is formulated as a linear optimization routine for N time steps in response to the RTP signal c_t, i.e.,

$$\min_{\boldsymbol{u}} \quad \sum_{i=1}^{N} c_i\, u_i\, \mathrm{P_c}\, \Delta t \qquad \text{s.t.} \tag{4.1}$$

$$SOC_{\min} \leq SOC_i \leq SOC_{\max} \qquad \forall i, \tag{4.2}$$

$$0 \leq u_i \leq 1 \qquad \text{for } i\text{, where vehicle is at home,} \tag{4.3}$$

$$0 = u_i \qquad \text{else.} \tag{4.4}$$

The control signal u_i defines the normalized charging power of the EVs. The energy constraint to maintain the state of the charge at minimum $SOC_{\min}$ and maximum $SOC_{\max}$ operational bounds is defined in Equation 4.2. The power constraints for the EVs are defined in Equation 4.3 to meet the charging current limitations either from the EV charging infrastructure or EV battery. The optimization routine having a horizon window of 36 hours is repeated after every 24 hours. An overlapping time window is chosen to ensure that the user's energy requirements are always fulfilled.

The load flow simulation is performed for a representative residential LV distribution grid in Austria for a simulation period of a week. The considered distribution grid is a weakly meshed residential grid with 49 nodes. The household load profiles and the mobility profiles are considered in the same manner as described in Chapter 3. Eight different scenarios with an EV penetration ranging from 10%-80% are assessed and compared, alongside a benchmark scenario consisting of no EVs. Day-ahead stock market prices from the Austrian electricity market (Energy Exchange Austria EXAA [45]) with a time resolution of 15 minutes are used as the incentive function in the optimization. The specifications for a Nissan Leaf are used to characterize the EV battery at a nominal charging power of 6.6 kW. The EV prediction data required for the optimization is assumed to be perfectly known.

4.2 Results and Discussion

The different performance indices reflecting both economic and systemic performance considered in the analysis are summarized in Table 4.1. Although the primary focus of the study is not the impact of uncoordinated charging on grid operations, the results illustrate the resulting negative implications of uncontrolled charging in the terms of power losses, PAPR, and voltage deviations. The results show a potential saving of about 30% per kWh in average energy costs relative to uncontrolled charging across all scenarios that reflect different penetration rates. This fact makes the method economically attractive for EV users.

Table 4.1: Results on optimization with RTP: An overview of the simulation results for the different scenarios, as well as uncontrolled (Unc) and optimized (Opt) operation of EVs, as published in Paper B

Scenario	Penetration rate (%)	Cost Savings per kWh (%)	PAPR		Power Losses		$V_{\min}$ (p.u.)	
			Unc	Opt	Unc	Opt	Unc	Opt
No EV	-	-	2.653		0.785		0.96	
1	10.4	30.77	2.545	2.550	0.8632	0.8605	0.95	0.95
2	20.8	30.74	2.477	2.976	0.9330	0.9348	0.93	0.93
3	31.3	31.28	2.457	3.564	1.0083	1.0214	0.93	0.92
4	41.7	30.80	2.703	4.174	1.0564	1.0840	0.93	0.90
5	52.1	30.89	2.732	4.754	1.1106	1.1525	0.93	0.89
6	62.5	31.42	2.875	5.054	1.1691	1.2333	0.93	0.89
7	72.9	31.55	3.082	5.424	1.2351	1.3219	0.93	0.89
8	83.3	31.62	3.592	5.760	1.3021	1.4176	0.92	0.89

A comparison of the total power at the transformer for 10% and 50% penetration for an example 24 hour time frame is shown in Figure 4.1. A penetration of 10% results in a reduction of the grid load of about 5%, while at 50% it results in additional load peaks up to 50%. The distortion to the natural stochastic nature of charging behavior in uncontrolled charging induced by these market-based ADSMs can therefore lead to more critical grid conditions at high EV penetration.

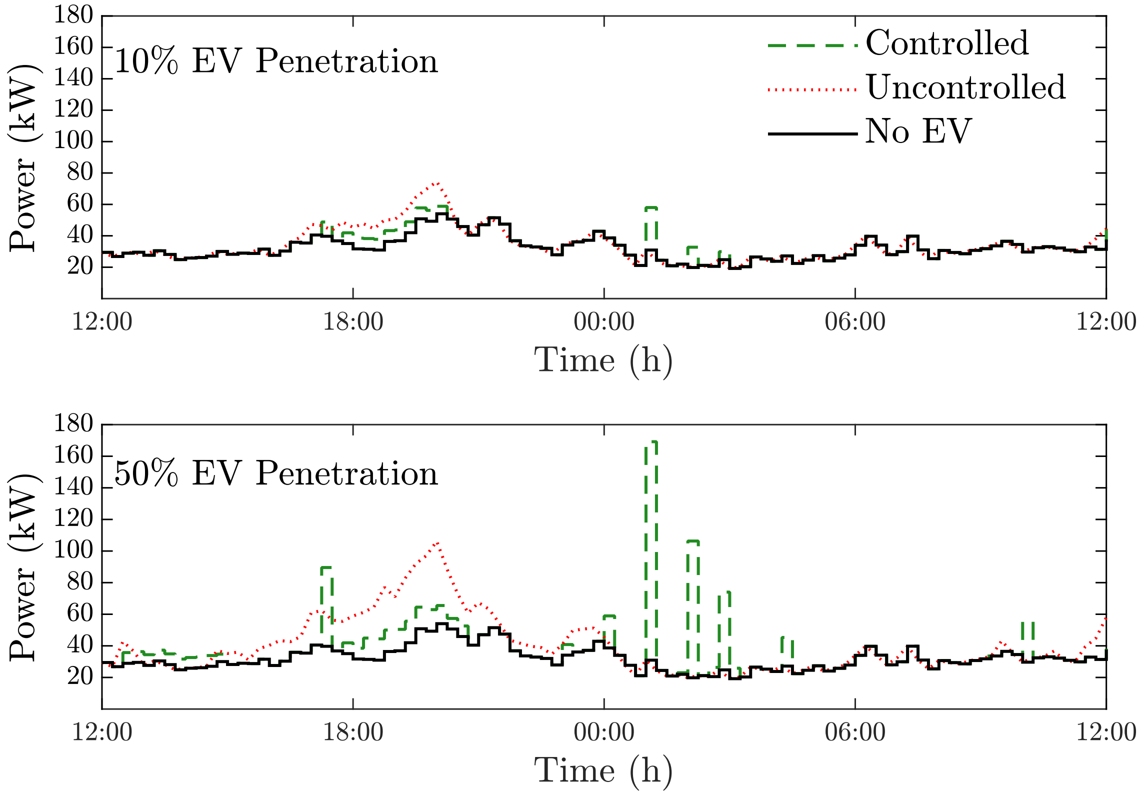

Figure 4.1: Effects of charging electric vehicles on the grid load

This effect of forming new peaks from the ADSM, which is referred to as the avalanche effect, is neglected in most studies. As EV penetration continues to increase, avalanche effects are likely to accelerate and could have a dramatic impact on system load and thus on the power system. While the majority of these studies draw a positive conclusion with regard to the effect of market-based DR for EVs, a limited number of studies analyze avalanche effects of demand, i.e. negative impacts of DR. Due to the expected high impact of EVs on system load, an avalanche effect triggered by EVs could have an incomparably stronger impact. Therefore, especially in the context of EVs, it is necessary to assess the incidence and systemic and economic impacts of avalanche effects and to develop DR methods to counteract them.

Chapter 5

ADSM based on Optimal Power Tracking

The uncoordinated charging of EVs leads to sudden high peaks in the load curve as discussed in the previous chapters. A more uniform load curve is favored for efficient operation and use of grid assets. Market-based DR strategies potentially can form unexpected new demand peaks and have strong impacts due to their high energy and power density. Therefore a DR strategy that avoids such negative effects and enables a grid-friendly integration of EVs is of high importance. DSM approaches with the objective of valley filling to achieve a smoother load curve are often discussed in the literature. However, achieving this goal without central coordination in a cost-effective way is worth further research. This chapter presents a decentralized ADSM method as proposed in Publication C, to achieve valley filling by exploiting the flexibility of the EV, which only requires unidirectional communication.

5.1 Optimal Power Tracking for Valley Filling

The fundamental principle of the decentralized method is to track a reference power signal, hence referred to as optimal power tracking (OPT) hereafter. The reference power signal is determined by a central entity to achieve valley filling through the exploitation of EV demand flexibility. The method is formulated in a two-layer architecture as presented in Figure 5.1, where the central entity (in the proposed study, the DSO) determines the tracking signal at the first layer, which is then broadcasted to all the grid-connected EVs. The controllers integrated into the EVSEs scale the received signal to their expected energy consumption for the following day and then track it with minimal deviations at the second layer. The optimal tracking problem is formulated in a linear form with the aim of achieving a reasonable near-optimal solution at reduced computational cost and resources.

The following sections present the details of the proposed method and the formulations of the optimization algorithms at each layer.

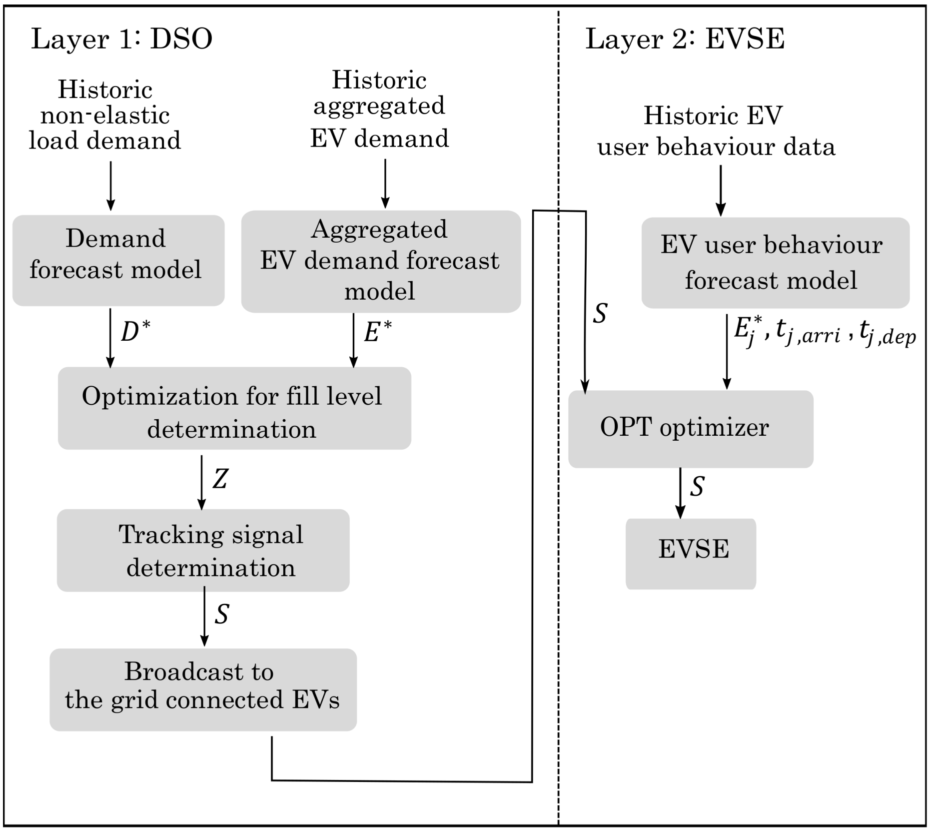

Figure 5.1: The two-layer architecture of the optimal power tracking demand side management algorithm for EV charging. In layer 1, the DSO determines a target power signal S based on the estimates of non-elastic power demand D^* and aggregated total EV demand E^* and broadcasts to all the EVs. In layer two, with the knowledge of EV user behavior estimates (arrival times $t_{j,\mathrm{arri}}$, departure times $t_{j,\mathrm{dep}}$, energy demand E_j^*), each EVSE performs an optimization to track the power signal received with minimal deviations.

5.1.1 First-layer: Optimization for Determining Tracking Signal

The tracking signal is determined based on the estimated day ahead aggregated non-EV demand profile (D^*) and the estimated total energy consumption of all the grid-connected EVs (E^*). The first step to determine the target signal is to obtain the fill level Z by solving,

$$\sum_{t=1}^{N^{\mathrm{T}}} \max\{(Z - D_t^*), 0\} \, \Delta t = E^*, \tag{5.1}$$

for Z using the two estimates in accordance with the classical water filling algorithm [46]. N^{T} is the total number of time steps of length Δt in the optimization window. The difference between the fill level Z and the estimated non-elastic load profile at each time interval D^* for the optimization horizon S_t is computed and transmitted to the EVs:

$$S_t = Z - D_t^*. \tag{5.2}$$

5.1.2 Second-layer: Optimization for Tracking the Reference Signal

In the second layer of the OPT, an optimization is performed by each local EV controller. The local controller attached to the EVSE splits the negative S_t^- and positive S_t^+ parts of the original power signal received S_t. The reference signal for the j^{th} EV,

$$S_{j,t}^+ = \frac{E_j^*}{\sum_{t=1}^{N^T} S_t^+ \, \Delta t} S_t^+ \tag{5.3}$$

is derived by scaling S_t^+ to the estimated next day energy demand for the j^{th} EV, E_j^*. The optimization routine is devised to track the S_t^+ with minimal deviation. The quadratic formulation of the above tracking problem is straightforward but computationally intensive. Furthermore, it has scalability problems as EV penetration progresses. To address this, a linear approximation to the original tracking problem is formulated as follows.

$$\min \sum_{t=1}^{N^{\mathrm{T}}} [a_{j,t}(1 + S_t^-) + b_{j,t}] \, \Delta t \qquad \text{s. t.} \tag{5.4}$$

$$-a_{j,t} \leq S_{j,t}^+ - P_{j,t} \leq a_{j,t} \qquad \forall j, \forall t, \tag{5.5}$$

$$-b_{j,t} \leq P_{j,t+1} - P_{j,t} \leq b_{j,t} \qquad \forall j, \forall t, \tag{5.6}$$

$$SOC_{j,\min} \leq SOC_{j,t} \leq SOC_{j,\max} \qquad \forall t, \forall j, \tag{5.7}$$

$$P_{j,\min} \leq P_{j,t} \leq P_{j,\max} \qquad \forall t, \forall j, \tag{5.8}$$

$$a_{j,t} \geq 0 \qquad \forall j, \forall t, \tag{5.9}$$

$$b_{j,t} \geq 0 \qquad \forall j, \forall t. \tag{5.10}$$

where $a_{j,t}$ and $b_{j,t}$ are two sets of auxiliary variables, $SOC_{j,\min}$ and $SOC_{j,\max}$ are the minimum and maximum permissible state of charge of the EV_j battery specified by the manufacturers. $P_{j,t}$ is the charging power of the EV_j at time t. $P_{j,\min}$ and $P_{j,\max}$ are the minimum and maximum permissible charging power of the battery, set by either the EVSE or EV manufacturer.

5.1.3 Centralized OPT Implementation

To benchmark the performance, a centralized DSM solution is implemented which has the same objective as the decentralized method presented. In contrast to the decentral implementation, the central counterpart track the power signal S_t^+ by exploiting the aggregated EV flexibility as given below,

$$\min \sum_{t=1}^{N^{\mathrm{T}}} (|S_t^+ - \sum_{j=1}^{N^{\mathrm{EV}}} P_{j,t}|(1 + S_t^-) + \sum_{j=1}^{N^{\mathrm{EV}}} P_{j,t+1} - \sum_{j=1}^{N^{\mathrm{EV}}} P_{j,t}|)\Delta t \tag{5.11}$$

subjected to the constraints (5.7-5.8).

5.2 Simulation Setup

A load flow simulation study is performed considering an Austrian LV distribution grid comprised of an 800 kVA, 10/0.42 kV step-down 3-phase transformer with 52 load nodes and 103 distribution lines. The grid supplies 490 residential consumers, 9 business units, and 77 other consumer units which include heat pumps, public facilities, etc. The residential loads, non-residential loads, and EV mobility profiles are modeled similarly to those described in Chapter 4. In the study, the most commonly used residential charging rate in Austria, i.e., 11 kW is considered. All the simulations are run on a server with an Intel(R) Xeon(R) CPU E5-2630 v3 @2.40 GHz processor and 31 Virtual CPUs. Load flow simulations for the considered distribution grid are performed over a week for ten different EV penetrations (10% -100%, in steps of 10%) for three scenarios; uncontrolled, centralized OPT, and decentralized OPT.

5.3 Results

The comparison of the different performance indices reflecting effectiveness in achieving the primary valley filling objective, computational run time, impact on EV user comfort, and impact on grid operation is evaluated for the simulated week. With increasing EV penetrations, the dimension of the state variables in the central OPT becomes very high, making the memory requirements of the optimization problem prohibitive. Given the high number of state variables at high penetration, the centralized OPT solution is realized only up to an EV penetration of 40% due to the limited memory capacity associated with the computational resources stated above.

The mean absolute deviation (MAD) between the valley fill level Z and the total demand D_t is defined as,

$$MAD = \frac{1}{N^{\mathrm{T}}} \sum_{t=1}^{N^{\mathrm{T}}} |Z_t - (D_t + \sum_{j=1}^{N^{\mathrm{EV}}} P_{j,t})| \ , \tag{5.12}$$

is used for comparing the effectiveness of the algorithm in achieving the objective.

As depicted in Figure 5.2, the centralized OPT performs better in realizing the objective of tracking the reference power signal. However, the insignificant discrepancy between the two confirms that the decentralized OPT even with less information exchange is capable of yielding a comparable result to the centralized OPT, offering a compelling alternative to centralized OPT.

A summary of the results including the key indices used for the evaluation at different penetrations is presented in Table 5.1. The indices such as PAPR, power losses, and cable overloading, which reflect network operation, indicate that the decentralized OPT formulation performs comparably to its centralized counterpart despite the reduced information exchange.

The charging rate which reflects the impact on user comfort is lower in the decentralized approach in comparison to the central counterpart. This is attributed to the loss of global information on the EV data in the decentralized implementation. Despite the lower charging rates, the decentralized OPT complies with the demanded energy delivery to all EVs as in the decentralized OPT.

Furthermore, the runtime of the two variants of the OPT exhibits a noticeable difference, where the runtime for the maximum feasible penetration with centralized OPT (i.e. 40%) is 400 minutes, while that of the decentralized variant is 12 minutes.

The results indicate that the proposed decentralized OPT method is a compelling alternative to centralized implementation for grid-friendly integration of EVs with no requirement for bidirectional communication and computationally intensive infrastructure.

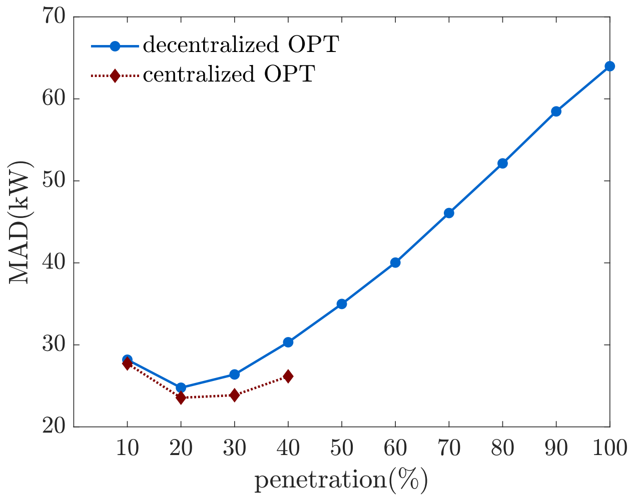

Figure 5.2: Mean absolute deviation between the valley fill level Z and the total demand for the centralized and decentralized OPT scenarios.

Table 5.1: The summary of the assignation details of EV to network nodes and the results representing key performance indices for the different EV penetrations.

Penetr-tion	**No of EVs**	**No. of nodes with EVs**	**PAPR**			**minimum voltage (p.u.)**			**maximum line loading (%)**			**power loss (kWh)**			**charging time (hours)**		
			Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D
0	0	0	1.83			0.96			89.7			517			0.72		
10	49	23	1.94	1.74	1.74	0.95	0.96	0.96	116.6	89.7	89.7	605	564	562	0.74	4.65	7.28
20	98	30	1.99	1.67	1.67	0.94	0.96	0.96	125.5	89.7	89.7	685	610	604	0.75	6.17	9.64
30	148	35	1.98	1.59	1.60	0.94	0.96	0.96	135.6	89.7	89.7	790	672	659	0.74	7.06	10.95
40	196	35	2.18	1.52	1.54	0.93	0.96	0.96	147.2	89.7	89.7	911	736	714	0.75	7.86	11.72
50	245	40	2.30		1.49	0.92		0.96	163.1		89.7	1016		763	0.74		12.10
60	293	45	2.30		1.45	0.92		0.96	169.9		89.8	1135		820	0.74		12.46
70	342	47	2.45		1.40	0.91		0.96	176.1		89.8	1242		867	0.74		12.79
80	392	48	2.48		1.35	0.90		0.96	191.7		89.9	1390		931	0.74		13.09
90	441	49	2.56		1.31	0.89		0.96	198.6		90.1	1526		991	0.74		13.34
100	490	52	2.69		1.32	0.87		0.96	205.7		90.2	1659		1045	0.74		13.40

Chapter 6

ADSM with IEC Compliant Charging Characteristics

The proposed ADSM algorithm described in the previous chapter (publication C) is well suited for practical implementations owing to its reduced computational costs and communication requirements. However, a variable charging (VC) rate, which is not in accordance with IEC charging standards, is assumed as reported in the majority of the literature, in validating the conceptual framework in publication C. This method is extended in Publication D by adopting a semi-continuous (SC) charging rate that complies with the charging standards defined in IEC 61851 which is either zero or varies between the minimum and maximum values. This chapter presents the mixed integer linear programming (MILP) formulation suggested to meet this requirement.

6.1 MILP Reformulation

The linear formulation to the optimization in the second layer of the architecture presented in Figure 5.1 is reformulated in a MILP formulation to achieve semi-continuous charging characteristics compliant with IEC standards. The objective and the associated constraints of the optimization problem are listed below, where j refers to the j^{th} EV.

$$\min \sum_{t=1}^{N^{\mathrm{T}}} \left[a_{j,t}(1+S^{-}_{t}) + b_{j,t}\right] \Delta t \qquad \text{s.t.} \tag{6.1}$$

$$-a_{j,t} \leq S^{+}_{j,t} - P_{j,t} \leq a_{j,t} \qquad \forall t, \forall j, \tag{6.2}$$

$$-b_{j,t} \leq P_{j,t+1} - P_{j,t} \leq b_{j,t} \qquad \forall t, \forall j, \tag{6.3}$$

$$SOC_{j,\min} \leq SOC_{j,t} \leq SOC_{j,\max} \qquad \forall t, \forall j, \tag{6.4}$$

$$x_{j,t}P_{j,\min} \leq P_{j,t} \leq x_{j,t}P_{j,\max} \qquad \forall t, \forall j, \tag{6.5}$$

$$x_{j,t} \in [0, 1] \qquad \forall t, \forall j, \tag{6.6}$$

$$b_{j,t} \geq 0 \qquad \forall t, \forall j, \tag{6.7}$$

$$x_{j,t} = 0 \qquad \forall j, \text{for } t, \text{ where the EV is not at home.} \tag{6.8}$$

Here, $a_{j,t}$ and $b_{j,t}$ are two sets of auxiliary variables, $SOC_{j,\min}$ and $SOC_{j,\max}$ are the minimum and maximum permissible state of charge of the battery of EV_j, specified by the manufacturers. The state of charge of vehicle j at time step t, $SOC_{j,t}$ is derived assuming a linear battery dynamics:

$$SOC_{j,t} = SOC_{j,0} + \frac{1}{C_j^{\mathrm{B}}}\Big\{\sum_{s=1}^{t} \eta_{j,\mathrm{c}}\, P_{j,s}\, \Delta t - \sum_{s=1}^{t} E_{j,s}\Big\} \tag{6.9}$$

where, $E_{j,t}$ refers to the energy demand for driving. $P_{j,t}$ is the charging power of the EV_j at time t. $P_{j,\min}$ and $P_{j,\max}$ are the minimum and maximum permissible charging power of the battery either defined by the EVSE or EV manufacturer. $x_{j,t}$ is a binary variable, which for each EV at time t specifies charging (1) or not-charging (0). It is used to implement the semi-continuous charging characteristics in compliance with the IEC standards for each EV_j at time t.

The limits imposed on the minimum charging current can result in new peaks due to simultaneity, especially at high penetrations. To mitigate this drawback, a randomization and a grouping mechanism are used in the decentralized controllers.

A grouping mechanism, implemented by the DSO, randomly assigns each EV to one of the N_g groups. A new target signal for each group $S_{g,t}$ is derived by segmenting the original target signal S_t into N_g signals, each exhibiting the same time integral reflecting energy. A given EV will receive the target signal created for the group and the total number of EVs present in the group ($N_{\mathrm{EV},g}$). Subsequently, the EVs perform the MILP optimization described above alongside a randomization process.

In the randomization process, each controller generates a random probability for every time slot of the target signal using a uniform distribution. Only if the probability is higher than a threshold value, charging is allowed. The threshold probability $P_{\mathrm{T},t}$ at time step t is determined based on the percentage of EVs in the group able to charge simultaneously at the minimum charge rate without exceeding the target signal:

$$P_{\mathrm{T},t} = 1 - \Big(\frac{S_{g,t}^{+}}{P_{\min} N_{\mathrm{EV},g}}\Big) \tag{6.10}$$

6.2 Simulation Setup

The distribution grid is modeled similarly to Chapter 5. The smart meter data set from the Irish Commission for Energy Regulation (CER) in a smart metering project is used to model the non-elastic household demand data [47]. These data having a half-hour sampling time are re-sampled to a sampling interval of 15 minutes. After filtering the incomplete data, a data set of 4225 customers is considered. The household demand data spans over a year from 14th July 2009 to 31st December 2010. This database with a larger data set is considered to capture a more generalized sample of consumers. The historical residential charging data are obtained from records of the experimental statistics of the Electric Charging Point Analysis project funded by the Office of Low Emission Vehicles [48]. The records include charging events spanning over a year for residential charge points in the UK. In contrast to the mobility profiles generated from the travel survey data, the charge point data set spans over a more extended time period which enables it to be used in prediction models to capture their dependencies. In this study, to demonstrate the feasibility of the concept, a perfect prediction of EV usage behavior and perfect predictions of non-elastic demands are assumed. Nine scenarios are considered in the analysis: A reference case with uncontrolled EV charging (Unc), a variable charge rate scenario as in previous studies with a linear formulation (VC), a semi-continuous charge rate MILP formulation with no grouping and randomization (SC), a MILP formulation with randomization and no grouping (SC_1), and MILP formulations with randomization and grouping from two to six groups (SC_2-SC_6).

6.3 Results

The primary objective of the method is to achieve valley filling utilizing the flexibility of the EVs. The variance of the demand profile is therefore used to evaluate the performance across different scenarios considered.

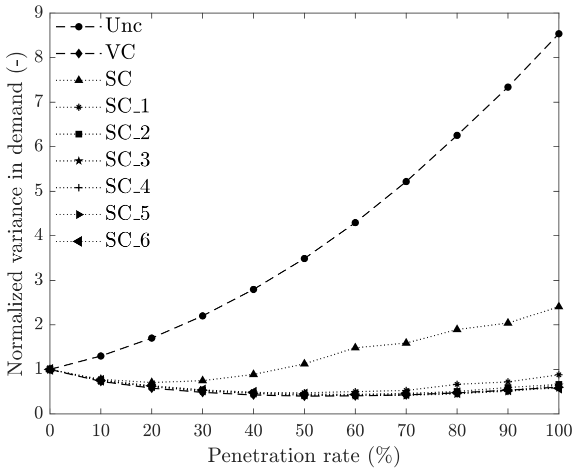

Figure 6.1: Variance in the total demand normalized to the variance of the 0% penetration for uncontrolled (Unc), OPT with variable charge rate (VC), OPT with semi-continuous charge rate (SC), OPT with semi-continuous charge rate and randomization in charging (SC_1), OPT with semi-continuous charge rate and randomized charging with two to six groups (SC_2-SC_6).

The formulation of OPT with SC charging alone reduces the variance in comparison to uncontrolled EV charging but shows a significant deviation from OPT with VC, which is more noticeable at high penetrations as observed in Figure 6.1. This can be attributed to the concurrent charging of a high number of EVs at the minimum permissible charging rate during the deep valley periods. The randomization process improves performance to a high extent across all penetrations, whilst still exhibiting a slight variation at high penetration. The inclusion of grouping leads to a performance much closer to the implementation of OPT with VC rate. Increasing the number of groups results in better performance, however, a group number of four is adequate to achieve similar performance to OPT with VC up to a penetration of 50%.

Chapter 7

Model Predictive Control Framework for Uncertainty Handling

The charging scheduling algorithms are often associated with multiple sources of uncertainty. However, the majority of the existing methods neglect these uncertainties making the assumption of perfect predictions. Adopting the same approach, the working principle of the proposed OPT approach is evaluated in publication C under the assumption of perfect predictions. Although few studies analyze EV scheduling problem considering uncertainty, most of them mainly focus on either the uncertainties arising from EVs or renewable generation. None of them incorporate the uncertainties stemming from multiple sources. To bridge this gap, publication E proposes a framework driven by model predictive control (MPC) considering multiple uncertainties to investigate the impact of various uncertainties on the expected objectives.

7.1 Uncertainty Modeling

The OPT method as depicted in Figure 7.1 is designed based on three estimates: 1) the non-elastic load demand 2) the aggregated demand of the EVs connected to the grid 3) the mobility behavior of the EVs. The non-elastic load demand and the aggregated EV demand estimates are needed at the first layer, being relatively trivial to obtain due to the aggregation. The mobility behavior is needed at the second layer, on a local basis for each individual vehicle, which can be attained by historic data. Since the scope of the study does not address the different forecasting methods, the known methods from the literature are employed to realize these estimates. The following sections provide a summary of the methods used to obtain these three estimates.

7.1.1 Non-elastic demand prediction model

Conventional mathematical techniques such as regression, exponential smoothing, stochastic time series, autoregression, autoregressive moving average, and support vector machine as well as soft computing techniques such as fuzzy logic, neural networks, and evolutionary algorithms are widely discussed in the literature for electricity demand forecasting based on historical data (which are summarized in [49, 50, 51, 52, 53, 54]). The intelligent transformer substations [55] in active distribution grids that are capable of measuring demand at short-term intervals are used more frequently by the DSOs and provide basic data to predict future demand.

Prediction methods based on neural networks, which are capable of approximating the non-linear functions in the data, have been considered in the proposed study since they demonstrate superior performance compared to conventional statistical-based methods. A long short-term memory (LSTM), a type of a recurrent neural network that is widely used for short-term demand forecasting is employed to predict non-elastic demand. Lagged demand data for 24 hours and other exogenous time-related variables (day of the week, month of the year, week of the month, time step of the day) are used as inputs for the neural network model. The model comprises four hidden layers and "Adam" optimization algorithm is used for training the data set.

7.1.2 Electric vehicle mobility behavior prediction model

A vital component of effective charging control algorithms is accurate estimations of the charging session parameters. These parameters are the start time, stay duration, and overall energy consumption and are necessary inputs for the scheduling algorithms. The OPT algorithm proposed in publication C depends on the estimates of these session parameters for each individual EV at the local customer level. A k-nearest neighbor-based approach is used to predict these session parameters, as it has been proven a valid approach to be effective in predicting usage demand for MPC-based DSM approaches in the field of water heaters [56]. To apply this approach, a time series of historic usage is created for each EV which includes the information on availability and driving energy demand by

$$D_t = \begin{cases} \frac{\sum_{t=t_1}^{t_2} E_{j,t}}{t_2 - t_1} : \text{unavailable at } t \in [t_1, t_2] \\ 0 : \text{available at } t \end{cases} . \tag{7.1}$$

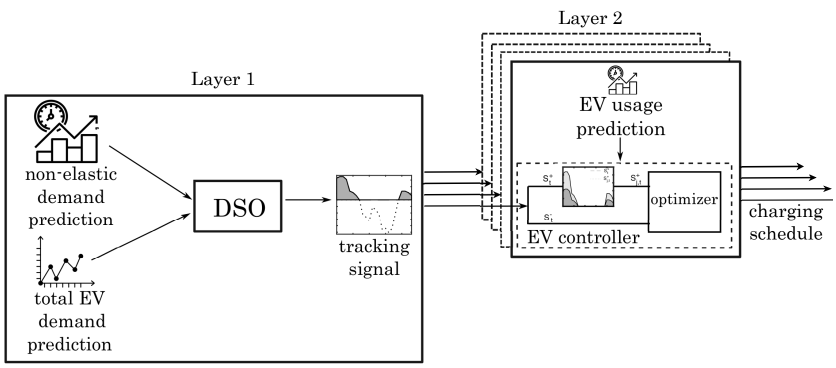

Figure 7.1: Two layer architecture of the optimal power tracking algorithm.

By comparison of the most recent time steps of usage data to historic daily usage data on the basis of Euclidean distance, the nearest neighbor is selected that complies with the availability at the current time step. $I_\mathrm{b} = 48$ time steps back is considered representing 12 hrs. $I_\mathrm{d} = \frac{24\,\mathrm{hr}}{\Delta t}$ yields an integer representing the amount of time steps spanned by one day. $l = 0$ and $l > 0$ represent the indices of current and historic demand time series. N steps forward in time are considered to be predicted, defined by the time steps considered for optimization. Then, the expected future usage is given by D^* according to:

$$\begin{aligned}
D_{\text{-}}^{(l)} &= \left(D_{t-lI_\mathrm{d}-I_\mathrm{b}}, \dots, D_{t-lI_\mathrm{d}}\right), 0 \le \ \le \left\lfloor \frac{t-I_\mathrm{b}}{I_\mathrm{d}} \right\rfloor \\
D_{+}^{(l)} &= \left(D_{t-lI_\mathrm{d}+1}, \dots, D_{t-lI_\mathrm{d}+N}\right), 1 \le \ \le \left\lfloor \frac{t-I_\mathrm{b}}{I_\mathrm{d}} \right\rfloor \\
l^* &= \mathrm{argmin}_{l>0} \| D_{\text{-}}^{(0)} - D_{\text{-}}^{(l)} \|, \text{ where } D_{t-lI_\mathrm{d}} = 0 \\
D^* &= D_{+}^{(l^*)}.
\end{aligned} \tag{7.2}$$

For implementation, MATLAB's Euclidean distance-based nearest neighbor algorithm [57] is used.

7.1.3 Aggregated EV energy consumption prediction model

A multilayer perceptron (MLP) model which is a class of feedforward neural networks is employed to determine the aggregated energy demand estimates of EVs. The historic EV demand data for the week before and the day of the week are used as input variables for training the model. A five-layer MLP model is used with the "Levenberg-Marquardt" algorithm as the training function.

7.2 MPC for Uncertainty Handling

MPC is a popular method primarily in the process control industry [58]. The principles of the MPC are equally applicable in the DSM domain to reduce the impacts of underlying uncertainties. In the MPC-based approaches, the optimal control sequence is determined at a given time instance for the optimization horizon. However, only the first samples of the deduced control sequence are applied. The aforementioned finite horizon optimization is re-iterated at a predefined time interval. By exploiting the latest available information, the method reduces the sub-optimality caused by estimation errors of uncertain parameters. MPC-based optimization processes are computationally intensive since they typically involve a multitude of computations due to the re-iterative nature of the method. The lower computational costs and faster run time offered by the distributed nature of OPT, render it a potential candidate for implementation in an MPC framework.

7.3 Results

Similar to the previous publications, a set of load flow simulations are performed for the purpose of evaluations. The household demand profiles and historic charging data are considered similar to Chapter 6. The performance of the proposed MPC framework for the OPT charge scheduling algorithm is evaluated considering the three sources of uncertainties discussed and compared to the ideal case with perfect predictions. The analysis focuses on two main aspects: 1) performance in achieving the primary objective of tracking the reference signal and 2) network-related performance indices. The comparative results include seven scenarios:

- Scenario A: uncontrolled charging
- Scenario B: variable charging assuming perfect predictions
- Scenario C: semi-continuous charging assuming perfect predictions
- Scenario D: MPC-based semi-continuous charging under load demand uncertainty
- Scenario E: MPC-based semi-continuous charging under EV user behavior uncertainty
- Scenario F: MPC-based semi-continuous charging under load and EV user behavior uncertainty
- Scenario G: MPC-based semi-continuous charging under load, aggregate EV demand, and EV user behavior uncertainty

The main results summarizing the performance indicators are presented in Table 7.1. The different uncertainties that are present in the system have different degrees of impact on the optimality of the scheduling algorithms. Comparing MAE, RMSE, and variance in Table 7.1, uncertainties related to user mobility behavior resulted in the most significant impact. The combined uncertainties do not indicate a summed impact, instead, the EV uncertainty dominates the overall effect. Despite the fact that the proposed MPC-based OPT method deviates from the perfect prediction scenario in achieving the objective, the variance in the aggregated demand curve is reduced by a factor of 4.8 in comparison to the uncontrolled scenario when both considered uncertainties are present. The relative reduction in the variance in scenario C with perfect predictions and IEC-compliant charging is a factor of 7.5. The network-related performance indicators in the MPC formulations show comparable results to that of the perfect predicted scenario. Hence, the method shows promising potential for demand response in EVs.

The study presented in Paper E, emphasizes the significance of incorporating uncertainty in the DSM methods for exploiting EV flexibility and suggests the MPC-based approach as a promising tool for EV charging scheduling problems under uncertainty.

Table 7.1: An overview of performance indicators for the seven scenarios considered.

Scenario	DSM	IEC compliance	Considered uncertainty: load uncertainty	Considered uncertainty: aggregated EV demand uncertainty	Considered uncertainty: EV usage uncertainty	MAE (p.u.)	RMSE (p.u.)	Normalized variance (p.u.)	PAPR	$\Delta V_{\mathbf{max}}(\%)$	No of overloaded cables
A	✗	✗	✗	✗	✗	0.1329	0.1569	3.1812	2.37	-10.17	11
B	✓	✗	✗	✗	✗	0.0314	0.0402	0.3734	1.40	-5.57	4
C	✓	✓	✗	✗	✗	0.0413	0.0545	0.4187	1.51	-6.12	4
D	✓	✓	✓	✗	✗	0.0453	0.0569	0.4848	1.54	-6.24	4
E	✓	✓	✗	✗	✓	0.0573	0.0689	0.6238	1.94	-9.53	4
F	✓	✓	✓	✗	✓	0.0576	0.0693	0.6403	2.03	-9.63	4
G	✓	✓	✓	✓	✓	0.0577	0.0695	0.6513	2.04	-10.46	5

Chapter 8

Conclusions

This thesis focuses on developing a conceptual framework of a techno-economic and practically viable autonomous DSM method to address the grid challenges arising from uncoordinated charging. The existing literature confirms that the flexibility of EVs has a high potential for providing DSM services. However, the majority of these studies are based on centralized control systems where communication is bidirectional. The expensive communication being the main drawback, these methods also suffer from scalability issues at high market penetrations. The decentralized approaches focusing on efficient, simple, cost-effective practically viable DSM solutions for EV charging are discussed sparsely. Hence the aim of this research work is to propose a decentralized charging scheduling algorithm for EVs which exhibits the aforementioned attributes.

To begin with, the feasibility of a communication-free charging control algorithm that has been discussed in the literature focusing on the reduction of voltage violations is analyzed and summarised in Chapter 3 (cf. publication A). The analysis conducted in the existing literature is limited to slow charging rates and a constricted range of penetrations. The systematic study presented in publication A, accounting for the typically available residential charging rates and covering the full range of penetrations, provides new insights into this domain of research. The results demonstrate that the method successfully mitigates voltage violation at slow charging rates for all penetrations. However, considering that the current market trend is leading to high nominal charging rates, the technical feasibility of the method is questionable at the high market penetration of EVs.

Publications B, C, D, and E propose and evaluate an ADSM algorithm for EV scheduling based on a signal originating from the utility. The main features of the proposed algorithm are as follows.

- The communication is strictly unidirectional. Therefore, more limited investments are required in the communication infrastructure.

- A two-layer hierarchical framework is proposed where the computational burden is distributed. Hence, the scalability at the high market penetrations is not a constraint.

- A linear approximation to the optimization is employed which exhibits a reasonable approximation to the original non-linear problem formulation. This feature resulted in reduced run time and computational cost. Consequently, required hardware specifications can be fulfilled with an embedded system that enables easy integration into the existing charging infrastructure.

- A semi-continuous charging characteristic is employed to comply with the IEC charging standards. Thereby enabling the economical operation of the EV battery as recommended by the manufacturers.

The proposed method, in contrast to the existing literature, is evaluated using simulation studies featuring the following aspects:

- Systematic time series load flow simulations;

- Realistic distribution grid topologies and demand profiles;

- Realistic EV mobility profiles;

- Wide range of EV market penetration.

Publication B investigates the feasibility of applying a market-based pricing signal to serve as the grid-originated signal. This paper draws the conclusion that the methods with simple pricing schemes tend to suffer from the avalanche effect forming new peaks in the demand curve. To mitigate this drawback, employing a power signal is suggested and optimization is formulated to achieve valley filling in the demand curve. The results indicate that the proposed method is techno-economically compelling for grid-friendly EV integration.

All the simulation studies carried out, with the exception of publication E, assume perfect predictions of the uncertain parameters. Nevertheless, in practice, these parameters have to be estimated and errors in estimation lead to suboptimal solutions. Most of the literature neglects the influence of uncertainties adhering to perfect predictions or only considers a single type of uncertainty. To bridge the gap, an MPC-based framework is proposed, as described in Chapter 7, which accounts for different sources of uncertainties on the EV user side and the network side. The results suggest that the EV mobility behavior estimates are the most critical. Furthermore, the results show that the proposed MPC framework provides a reasonably robust solution against these uncertainties.

Driven by technological advancements and worldwide awareness of sustainability, the market penetration of EVs is on the rise, offering both challenges and opportunities for the electricity network. The managed charging shows a high potential for relieving the stress on the grid. However, the costs associated with these amenities must be weighed against the rewards they offer. The proposed method in this thesis can be considered a cost-effective solution that can be deployed with reduced infrastructural upgrades and offers distribution grid operators a convincing solution for the grid-friendly integration of EVs.

Chapter 9

Outlook

The current energy system is transforming into a more complex system integrated with intermittent distributed generation, high power and energy-intensive consumer loads such as EVs and heat pumps, and increasing participation of prosumers. Sustaining the stability of the grid is becoming an increasingly challenging task with these new developments. Integration of advanced technologies in smart grids enables these challenges to be seen as opportunities. EV loads exhibit a high potential in offering opportunities for the provision of grid services through DSM methods owing to their temporal flexibility and high energy density. In the scope of this work, an ADSM method for charging scheduling is proposed and validated with simulation studies. However, the design of communication protocols between smart meters, charging equipment, and programmable logic controllers (PLC) for implementation and testing is an essential aspect for further development. The author with her colleagues has initiated investigations into this area.

The proposed scheduling algorithm in this thesis is only limited to load-shift potential. However, the method could be further extended to provide V2G services. Within the scope of this thesis, a simplistic linear battery dynamics is assumed. However, with the inclusion of the V2G services, a more detailed battery model describing the state of charge dependant charging behaviors and degradation from the cyclic charging events is of importance. Accordingly, the proposed method can be extended to account for these aspects. Furthermore, the incentives for consumer participation in providing grid services and the policy framework for the implementation in practice remain to be developed by the DSO.

Across Europe, there are new regulations emerging for multi-residential complexes where charging facilities are mandatory. The charging scheduling algorithms for charging scheduling of EV fleets in these facilities are a potential research question.

Due to the current trends in the energy sector, the interests of the utility, as well as consumers, are gaining toward distributed generation. Photovoltaic (PV) systems are becoming increasingly popular. The author together with her colleagues investigates the quantification methods for hosting capacities in distribution grids as discussed in Publication F. Concomitantly, developing a management algorithm for a system where PVs and EVs interact is an interesting research direction. Furthermore, the integration of the flexibilities of the thermal and electrochemical energy storage systems is a potential extension.

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PART II

Publications

Publication A

Author Contribution

- Literature survey of voltage-based droop control of EV charging
- Concept of the simulation method
- Implementation of the simulation software in MATLAB and evaluation
- Analysis of the results
- Manuscript preparation

energies

MDPI

Article

Voltage-Based Droop Control of Electric Vehicles in Distribution Grids under Different Charging Power Levels

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Abstract: If left uncontrolled, electric vehicle charging poses severe challenges to distribution grid operation. Resulting issues are expected to be mitigated by charging control. In particular, voltage-based charging control, by relying only on the local measurements of voltage at the point of connection, provides an autonomous communication-free solution. The controller, attached to the charging equipment, compares the measured voltage to a reference voltage and adapts the charging power using a droop control characteristic. We present a systematic study of the voltage-based droop control method for electric vehicles to establish the usability of the method for all the currently available residential electric vehicle charging possibilities considering a wide range of electric vehicle penetrations. Voltage limits are evaluated according to the international standard EN50160, using long-term load flow simulations based on a real distribution grid topology and real load profiles. The results achieved show that the voltage-based droop controller is able to mitigate the under voltage problems completely in distribution grids in cases either deploying low charging power levels or exhibiting low penetration rates. For high charging rates and high penetrations, the control mechanism improves the overall voltage profile, but it does not remedy the under voltage problems completely. The evaluation also shows the controller's ability to reduce the peak power at the transformer and indicates the impact it has on users due to the reduction in the average charging rates. The outcomes of the paper provide the distribution grid operators an insight on the voltage-based droop control mechanism for the future grid planning and investments.

Keywords: electric vehicles; demand response; demand side management; voltage-based droop control; distribution grids; voltage violations

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1. Introduction

The electrification of the transportation sector provokes many challenges in the power system operation, most notably in the low voltage (LV) distribution networks [1–3]. If left uncontrolled, private electric vehicles (EV) are more likely to be charged at high coincidence when most of the EV owners return home from their work. As a result, EV charging raises the already existing peak demand at the distribution transformers in this period leading to many operational problems: voltage drops; increased power losses; increased probability in overloading of distribution transformers and cables; higher risk of service interruptions [1,2,4–8]. Demand side management (DSM) strategies exploit the flexibility of EV charging to reduce these adverse impacts on the grid operation [9–12]. In this manner, DSM approaches enable the efficient use of existing network capacity and reduce the cost-sensitive grid reinforcements even at high EV penetrations.

Voltage-dependent charge control methods are discussed as a feasible solution for the voltage deviations arising from EV charging [6,13–16]. Depending only on local voltage measurements at the point of connection, these controllers work on a simple droop control mechanism, which can be easily installed in already existing electric vehicle supply equipment. In contrast to other approaches, a voltage dependent control mechanism demands no communication infrastructure [17]. It can be easily integrated into the existing network at low costs and is robust as it is not subject to potential communication failures. The potential of this approach to improve grid voltage profile has been demonstrated using LV distribution grid simulations. Relevant publications are reviewed hereafter, an overview of the referenced work and existing approaches in literature being provided in Table 1.

Table 1. An overview of literature on voltage-based charging control and the proposed study.

Ref.	Penetration	Nominal Charging Power (kW)
[6]	50 %, (60 %, 70 %)	6.6
[13]	10 EVs	4
[14]	39 EVs	3.3
[15]	43 EVs	3.7
[16]	80%	undefined
[this paper]	5%, 10–100% (in steps of 10%)	3.3, 6.6, 11

The impact of the voltage droop charging method for EVs in a large LV residential grid comprised of 1020 households is assessed by Al-Awami et al. [6]. The authors consider three different EV penetrations (50%, 60%, 70%) assuming a charging power of 6.6 kW. The mobility behavior of the EVs are modeled using a Gaussian distribution. Voltage variations in extreme nodes, average charging time and total loading in the grid are evaluated for a period of a single day. The results indicate that this method is capable of eliminating the voltage violations caused by EV charging in cooperation with voltage control devices.

Geth et al. [13] evaluate the voltage droop charging method in a residential feeder for two scenarios. In the first scenario, only one out of 20 EVs is controlled by the droop mechanism. In the latter, all EVs are controlled by the droop mechanism. The paper demonstrates the potential voltage improvements with droop controlling in a distribution grid and evaluates the impact on the average charging rates. Comparing the two scenarios, the authors conclude that the effectiveness of the method improves with increasing number of controlled electric vehicles.

Leemput et al. [14] evaluate the voltage droop method for EVs using long-term simulations (for a period of a half year), considering a scenario with a total number of 39 EVs and a charging power of 3.3 kW. The LV grid model consists of a main feeder with 39 households and five other parallel feeders. These parallel feeders are modeled in a simplified manner with a total load equal to the aggregated load of the main feeder. The compliance with the EN50160 voltage standards [18], charging time of the EVs and the maximum transformer power are discussed in detail in the results. The authors conclude that the impact on the charging time is very limited and, the droop control alone does not provide the results in compliance with the EN50160 standard.

Álvarez et al. [15] study four voltage dependent solutions for controlling the charging of EVs in a real Danish network. The network consists of a main feeder with 43 households and three other feeders that are represented by a single aggregated load. 43 EVs and a maximum charging power of 3.7 kW are considered. The simulations are conducted assuming a typical winter day, i.e., a high load case. The impact of the proposed methods on the voltage profiles of several important nodes are analyzed in the paper. They conclude that a simple droop controller together with a hysteresis comparator improves the power quality of a power system.

An analysis on the voltage droop charging method for EVs on a Victorian LV grid with an EV penetration of 80 % is presented by Xia et al. [16]. The voltage improvements on all the nodes and the total grid power are evaluated for a single day.

Three-phase home charging with 11 kW power is now preferred in most European countries, owing to the availability of three-phase electricity at households. None of the available research investigates the applicability of the voltage droop control mechanism for 11 kW EV charging. Therefore, it is unclear whether the conclusions drawn hold equally with regard to 11 kW charging. Furthermore, most of the references discussed, only evaluate the results for a small set of EV penetrations. Except the work by Leemput et al. [14], which considers a simulation time of half a year, the presented publications base their results on single day or weekly simulations. Only the authors in [14] present a comprehensive analysis on the voltage profile and evaluate the compliance with the voltage magnitude standards as defined in ENE50160. Therefore, no comprehensive assessment on the benefits and limitations of the voltage-based control for charging EVs in a distribution grid has yet been provided. Our goal is to find, if the LV distribution grids are able to comply with the voltage magnitude standards with droop controlled EV charging for all combinations of penetrations and currently available residential charging power levels. To this end, we present a systematic study of voltage-based EV charging control, taking into account:

- three currently available charging power levels (3.3 kW, 6.6 kW, 11 kW);
- a full range of EV penetrations (5%, 10–100%, in steps of 10%);
- long term simulations (half a year);
- real distribution grid topology and load data.

We present our results including an assessment of:

- the voltage magnitude compliance with the standards;
- the peak power in the grid;
- the average charging rates over a range of EV penetrations and three charging power levels.

The rest of the paper is structured as follows: Section 2 describes the concept of the voltage-based charging controller, as well as the simulation framework used to evaluate the voltage-based charging control method; the results are presented in Section 3, followed by a conclusion in Section 4.

2. System Modeling

2.1. Voltage Based Controller Characteristics

Reducing voltage deviations stemming from EV charging, and, thereby improving the voltage profile of distribution grids, is the main objective of the voltage-based control approach considered. To facilitate the control mechanism, it is assumed that each EV charging infrastructure is equipped with a droop controller accompanied by an advanced metering infrastructure (AMI) at the point of connection [19] capable of measuring the voltages. The general concept of the voltage droop mechanism is depicted in Figure 1.

The measured voltage of the AMI at the point of connection serves as input to the voltage droop control mechanism. The charging current of the EV is set according to the droop characteristics, as shown in Figure 2.

$$I(V) = \begin{cases} I_{\text{min}}, \ V \leq V_{\text{ref},1} \\ I_{\text{max}}, \ V \geq V_{\text{ref},2} \\ I_{\text{min}} + \dfrac{V - V_{\text{ref},1}}{V_{\text{ref},2} - V_{\text{ref},1}} (I_{\text{max}} - I_{\text{min}}) \text{ , else.} \end{cases} \tag{1}$$

As defined in Equation (1), if the node voltage V, measured at the point of connection, falls below the lower reference value $V_{\text{ref},1}$, the charging current I is limited to the minimum charging current I_{min}. According to the IEC-61851 EV charging standards, this is to be 30% of the rated charging current. If the node voltage exceeds the upper reference value $V_{\text{ref},2}$, the charging is not limited by the controller and allowed to be carried out at the maximum current I_{max}. This limit for charging current is determined based on the nominal charging power levels. If the voltage lies between the lower and upper voltage reference values, the charging current is controlled in accordance to the linear droop characteristics.

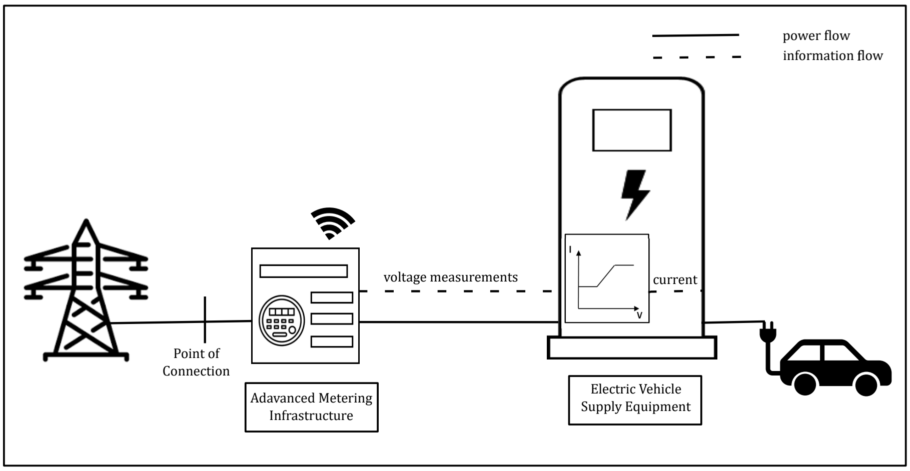

Figure 1. Voltage droop control mechanism.

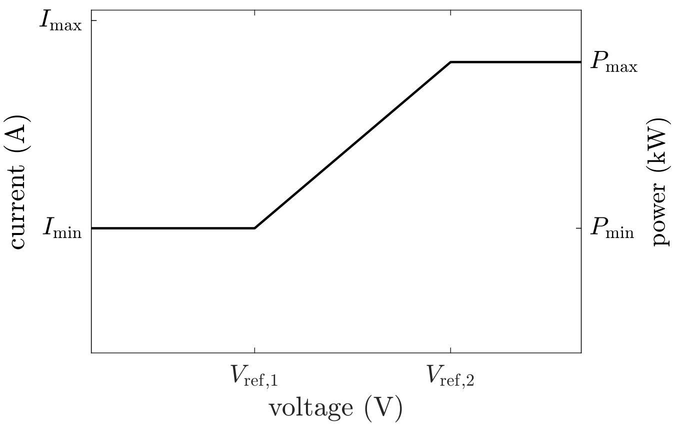

Figure 2. Voltage droop characteristics for EV charging current control.

2.2. Simulation Framework

The topological data and grid parameters of a real Austrian distribution grid were provided by the local distribution system operator (DSO), Vorarlberger Energienetze GmbH [20]. The simulated LV grid comprises two 630 kVA, 10/0.42 kV step down 3-phase transformers with 221 load nodes. The grid supplies 600 residential consumers, 52 business units, and 99 other consumer units which include heat pumps, public facilities, etc. Figure 3 shows the geographical representation of the simulated LV network.

An in-house simulation tool [21] for load flow simulations is used. It is implemented in MATLAB [22] and provides interfaces to implement DSM strategies for flexible devices and energy storage systems. The load flow calculation is implemented using the backward forward sweep flow method as proposed by Ghatak and Mukherjee [23]. For the load flow calculation, the load currents are calculated in the backward sweep and the bus voltages are calculated in the forward sweep based on the currents determined. The process is repeated until convergence of node voltages with respect to a limiting tolerance value. To map the voltage-base control of EVs, in each iteration the charging current is calculated according to the droop control characteristics. In our study, we conducted a balanced three-phase load flow simulations with a time resolution of 15 min for randomly chosen 25 weeks in the winter season, where the electricity demands are typically high.

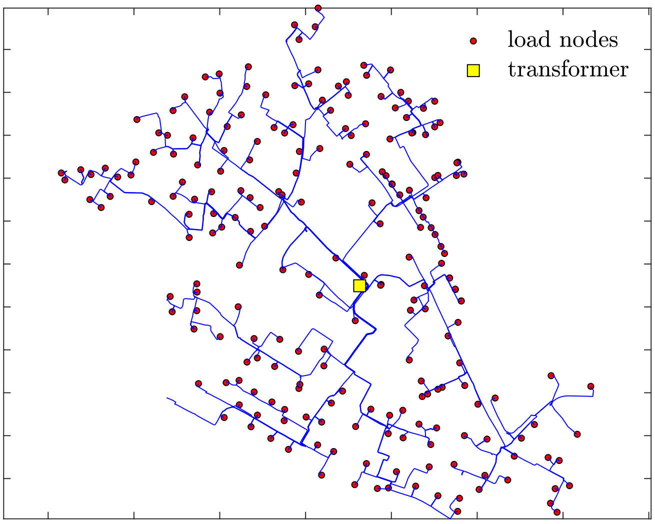

Figure 3. LV distribution grid model.

Residential loads are modeled using real smart meter data recorded in a field test by the local energy provider illwerke vkw AG (VKW) [24]. The consumption data over a year for 351 households with a time resolution of 15 min were available. The smart meter data are assigned to the household loads by mapping the annual energy demand. Non-residential loads are modeled using standard load profiles of the Austrian clearing and settlement agency [25]. These standard profiles are scaled in accordance with the annual energy demand of a specific consumer. The power factor for the loads was tuned to 0.98 based on active and reactive power measurements at the substation.

Existing PV generations with an installed capacity of 5.96 kWp are considered in the simulation. Typical PV power profiles from the region of the grid with a 15-min resolution are used and scaled to match the installed capacity of a particular PV installation.

2.3. EV Model

A linear model is used to characterize the system dynamics of the EV battery. The energy content of the EV battery at time t, $E(t)$ can be expressed mathematically by

$$E(t) = E(t-1) \; + \eta_\text{c}\, P^{(\text{c})}(t)\Delta t \; - P^{(\text{d})}(t)\Delta t, \tag{2}$$

where $E(t)$ is the time dependent energy content of the battery, $P^{(\text{c})}(t)$ is the charging power and $P^{(\text{d})}(t)$ is the discharging power at time t. η_c is the charging efficiency of the charging equipment and Δt is the time step. The model neglects the standby losses of the battery.

The state of charge of the ith EV at discrete time step n is given by

$$SOC_{i,n} = SOC_{i,0} + \frac{1}{C_i}\left\{\sum_{t=1}^{n}\left(\eta_\text{c}\, P^{(\text{c})}_{i,n}, -P^{(\text{d})}_{i,n}\right)\Delta t\right\}$$
$$\forall n = 1,\dots,N, \forall i = 1,\dots,I. \tag{3}$$

$SOC_{i,0}$ and $SOC_{i,n}$ refer to the initial SOC and the SOC at time step n of the ith EV, respectively. C_i is the battery capacity of the ith EV. N is the total number of time steps and I is the total number of EVs present.

The battery capacity of an EV is set to $C_i = 24$ kWh which corresponds to a Nissan Leaf [26]. The charging efficiency is set to $\eta_c = 0.9$. Three currently available residential nominal charging power levels were considered in the study: $P^{(\text{c})}_{\text{max}} = 3.3$ kW, 6.6 kW, 11 kW.

The EV usage behavior is modeled using the statistical data from the Austrian national mobility survey conducted in 2013 [27]. The survey provides detailed data on the departure and arrival times, as well as the distances traveled for all journeys recorded. Based on these data, the user behavior profiles are generated, which include energy consumption and availability for charging at each time step. The energy consumption is computed based on the distances driven and the duration of the journey, assuming a specific energy consumption of $\eta_d = 0.15$ kWh/km [28]. Furthermore, it is assumed that the vehicle is available at home before it departs for the first trip and after it returns from the last trip of the day. The entries with long daily distances are excluded from the data to comply with the electric ranges of the EVs. Moreover, it is assumed that the EV charging is controlled only at private charging infrastructure. The 15-min based usage profiles for EVs are generated by taking the differences in weekend and weekday journeys into account. After cleaning the data of the available on the survey, 15,320 weekday and 5696 weekend driving profiles were created and used as a library for usage behavior modeling. These profiles were assigned for the EVs randomly.

The EVs are randomly assigned to the network nodes for a given penetration, with a maximum of one EV per household. The same random pattern is kept over all the scenarios to assure the consistency. At each subsequent penetration the new EVs are progressively added to the existing EV fleet.

2.4. Scenarios

To evaluate the implications of the droop control charging on grid operation, several scenarios were simulated. An overview is given in Table 2.

Table 2. Overview of the scenarios considered in the simulations: benchmark scenario (BM), uncontrolled scenarios (U1–U3) and controlled scenarios (C1–C3) for three different charging power ratings each.

Scenario	Nominal Power (Kw)	Description
BM	-	benchmark, no EVs are connected to the grid
U1	11	EVs charge at nominal power as soon they arrive home
U2	6.6	EVs charge at nominal power as soon they arrive home
U3	3.3	EVs charge at nominal power as soon they arrive home
C1	11	EVs charging with voltage droop control
C2	6.6	EVs charging with voltage droop control
C3	3.3	EVs charging with voltage droop control

For all the six scenarios except the benchmark scenario, eleven EV penetrations (5%, 10–100%, in steps of 10%) were considered, resulting in a total of 67 grid simulation runs over a time horizon of half a year.

The reference voltages for the voltage-based controller are set to $V_{\mathrm{ref},1} = 0.92$ p.u. and $V_{\mathrm{ref},2} = 0.96$ p.u. to comply with the voltage magnitude standards specified in ENE50160. The lower voltage reference limit was chosen to account for the maximum possible voltage drop in the cable connecting the load node to the charging controller.

3. Results

The plausibility of voltage-based control for EV charging in complying with the voltage magnitude standards was investigated for different charging power levels and a full range of EV penetrations. The analysis was performed considering several aspects, separately discussed in the sections hereafter: the compliance with the voltage magnitude standards defined in EN50160; the normalized charging rate; the peak power at the transformer; a statistical analysis on the nodal voltages.

3.1. Compliance of the Voltage with the International Standard EN50160

For the satisfactory operation of the customer electrical equipment, the voltage magnitude should be maintained within a regulated range. The European standard EN50160 specifies that the 10-min rms value of the supply voltage in LV distribution networks should not deviate from the nominal value more than 10% for 95% of the time within a week. Additionally, the 10-min rms values of the supply voltage has to remain in the range of $[-15\%, +10\%]$ in any case. The first condition will be referred to as the time limit, the latter to as the minimum and maximum voltage limit, respectively.

To investigate the impact of the droop-control on the voltage magnitude, we evaluated the compliance with the voltage magnitude standards defined in EN50160 as described above. The evaluation is conducted on a weekly basis for the 25 weeks simulated. Figure 4 shows the maximum duration of the rms values of the nodal voltages exceeding a -10% of the nominal voltage value and the violations of the -15% voltage limit. Table 3 summarizes the voltage compliance for the two conditions (time and voltage limit) defined in the EN50160 standard for the six scenarios.

Table 3. Compliance with the EN50160 voltage standards for the six scenarios (uncontrolled U1–U3 and controlled C1–C3) for the range of penetrations; $-/-$: compliant with the time limit and compliant with the minimum voltage limit; $-/+$: compliant with the time limit and violation of the minimum voltage limit; $+/-$: violation of the time limit and compliant with the minimum voltage limit; $+/+$: violation of the time limit and violation of the minimum voltage limit. Shaded text is used to highlight the mitigation effects achieved by the droop controller.

Scenario	**Penetration (%)**										
	5	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
U1	−/−	−/−	−/−	−/−	−/−	−/+	−/+	−/+	+/+	+/+	+/+
C1	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/+	−/+
U2	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/+	−/+	+/+	+/+
C2	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−
U3	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/+	−/+	+/+
C3	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−	−/−

As illustrated in the bottom plot of the Figure 4, the voltage deviation exceeds the -10%-limit already in the benchmark scenario (without EVs). Nevertheless, the grid voltage is in compliance with the EN50160 voltage standards as the maximum duration below the -10%-limit is less than 5% of the time. The compliance with time limit is met in all the scenarios up to 70% penetration as illustrated from the top plot of Figure 4, however, utilization of the available voltage reserves grows steadily with increasing penetration for the uncontrolled scenarios (U*), most notably in the scenario U1 (uncontrolled 11 kW-scenario). In contrast, the minimum voltage deviation exceeds the -15%-limit already at lower penetrations, resulting in a violation of the voltage limit defined in the ENE50160 standards. Specifically, at 50% penetration in case of 11 kW (U1) followed by 6.6 kW (U2) at 70% penetration, and 80% for the 3.3 kW (U3) charging rate.

With 11 kW charging power level, the droop controller (C1) eliminates the time and voltage limit violations for 50%–80% penetrations, ensuring the compliance with the EN50160 voltage standards up to 80% penetration. For the penetrations above 80%, the controller is not capable of eliminating the violation of the -15%-limit (voltage limit) anymore. With 6.6 kW and 3.3 kW scenarios (C2, C3), the droop controller mitigates the time and voltage limit violations successfully, and ensures the voltage compliance with the EN50160 standard for penetration rates where it is violated in case of uncontrolled charging, cf. Table 3.

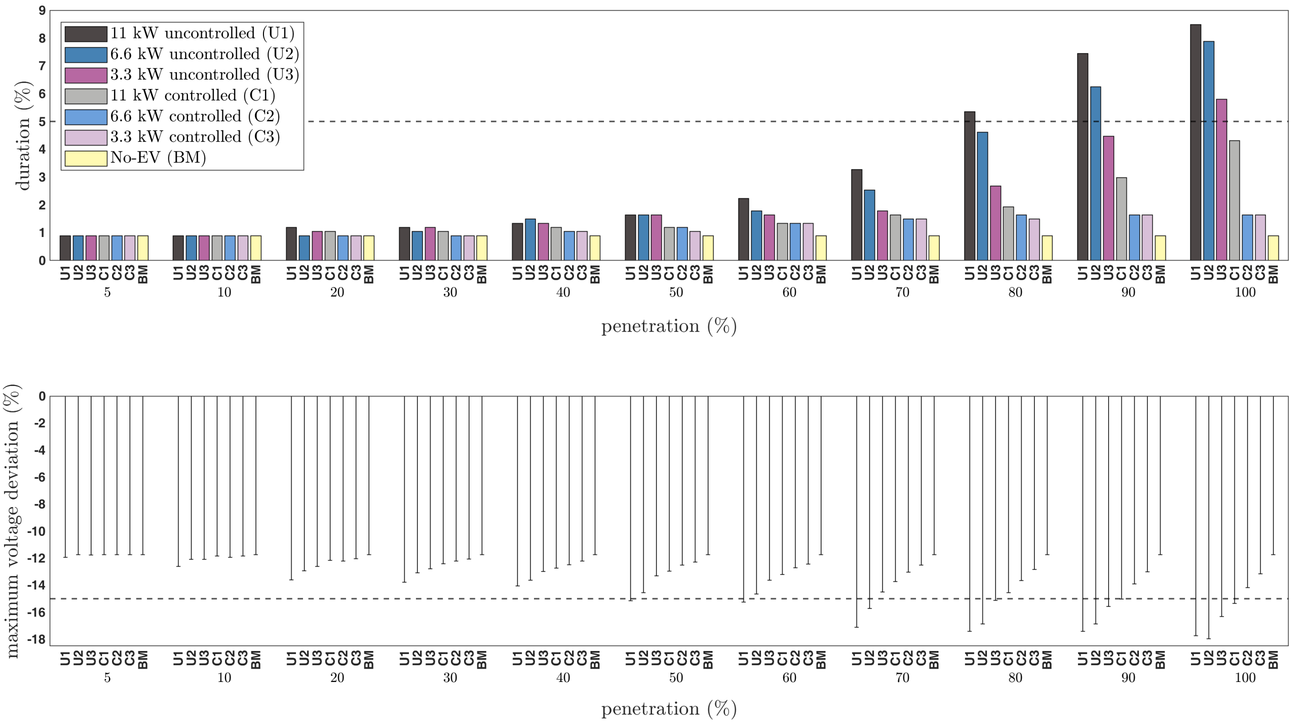

Figure 4. Maximum duration of the rms voltage deviation below the −10% threshold (**top**), minimum voltage deviation (**bottom**) for the benchmark case (BM), the uncontrolled (U1–U3) and controlled (C1–C3) scenarios. The dashed lines show the threshold limits defined in the EN50160 standard.

The outcomes of Leemput et al. [14] states that the droop controlling fails to meet the time limit defined in ENE50160 for a EV charging rate of 3.3 kW at 100% penetration. In contrast, the results of this research show that the droop controlling assists in complying with the defined time limit at this charging rate. The reason for this discrepancy is the differences in the voltage reference points in the controller. The authors in this paper use a lower and upper voltage reference point of 0.85 p.u. and 0.90 p.u., respectively. In contrast, we use a more restricted set of reference points, with the lower and upper reference points being set at 0.92 p.u. and 0.96 p.u., respectively.

The results indicate that at high charging power (11 kW) and at high penetrations (at 90% and above), although the controller does not contribute to the compliance with the minimum voltage limit, i.e., −15%, the compliance with the time limit is achieved. However, even in these cases the grid voltage is very close to the threshold limits. Furthermore, even the controlled scenarios with low charging power levels approach the minimum voltage limit, at high penetrations, exhibiting a reduced voltage reserve. Therefore, DSOs should be aware of the fact that though the method is well suited to mitigate the voltage problems when charging at low power levels and low penetrations, it does not provide a full assurance at high charging power levels and high penetrations.

3.2. Average Charging Rate

In order to estimate the impact on the user comfort due to prolonged charging times caused by the control mechanism, the relative average charging rate was examined. Table 4 summarizes the average charging power normalized to the respective nominal charging power for the scenarios and penetrations considered. Already for the case of lowest load increase (3.3 kW charging rate at 5% penetration), a significant impact with a reduction of 20% is observed with the controlling. In the extreme case of a high charging power of 11 kW and full EV penetration, a noticeable impact on the charging rate of 57% is observed. For the increasing penetrations from low 5% to high 100%, the average charging rate reduces by over 10% for all the charging power levels considered.

Table 4. Normalized average charging rate for the droop controlled scenarios (C1–C3).

Penetration (%)	C1	C2	C3
5	0.67	0.74	0.80
10	0.65	0.72	0.79
20	0.65	0.71	0.78
30	0.64	0.71	0.78
40	0.64	0.70	0.77
50	0.63	0.69	0.76
60	0.62	0.69	0.75
70	0.61	0.67	0.74
80	0.60	0.66	0.72
90	0.59	0.64	0.71
100	0.57	0.62	0.69

3.3. Peak Power

As a consequence of the changes in the charging demand due to the intervention of the controller, the power profile at the transformer changes, which, in turn, affects the peak power. To show this effect, the peak power and the relative reduction in the peak power at the transformer resulting from the droop controlled charging are depicted in Figure 5. Peak power increases with progressive EV penetration in all six scenarios. At high penetrations, the peak power exceeds the transformer rated capacity in the uncontrolled scenarios (U*). In the voltage droop controlled scenarios, a consistent reduction in relative peak power at the transformer could be noticed: from 1%, over 3% , up to 12% for the different penetration rates of 5%, 50%, and 100%, respectively. This shows that in addition to the voltage regulation services provided to the DSOs, the method provides a reduction in peak power at the transformer, preventing potential transformer upgrades.

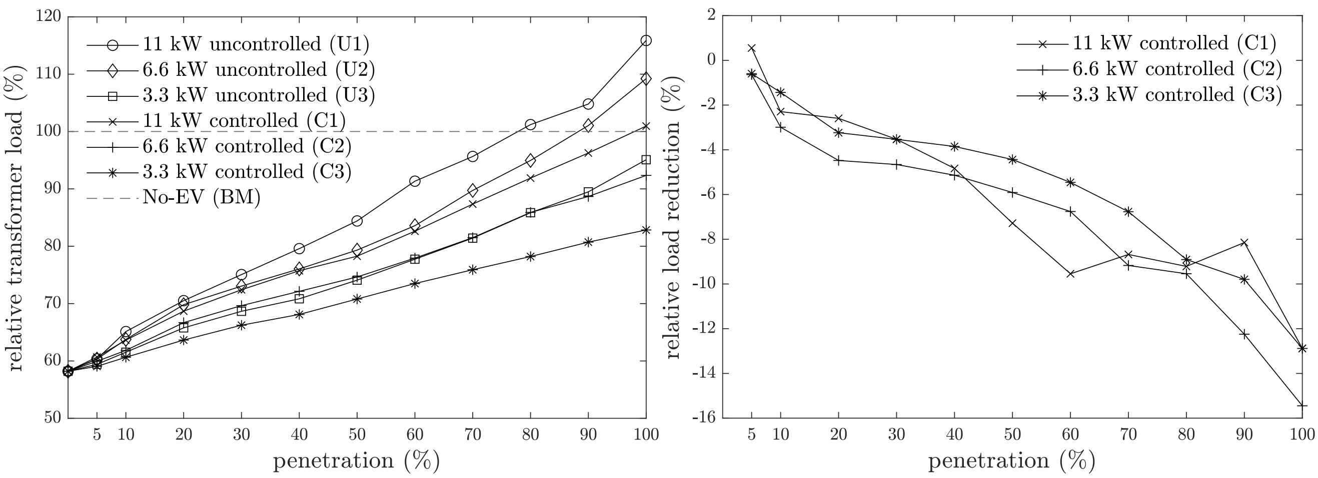

Figure 5. Maximum relative peak power at the transformer for the six scenarios (**left**), relative reduction in the peak power at the transformer by the voltage droop controlling (**right**).

3.4. Nodal Voltages

We conducted a quantitative analysis of the number of under voltage events in order to gain a more in-depth understanding of the voltage droop control. The histograms in Figure 6 compare the number of under voltage events for the six scenarios at 10% and 90% penetration. The histograms show that the number of under voltage events has been reduced in the three droop controlled scenarios (C1–C3) for both penetrations. In addition, the evaluation confirms the elimination of severe under voltage events due to the droop control, which occur in uncontrolled charging at high penetrations. Furthermore, it clearly shows the direct dependency of the relative reduction in under voltage events on the EV penetration rate.

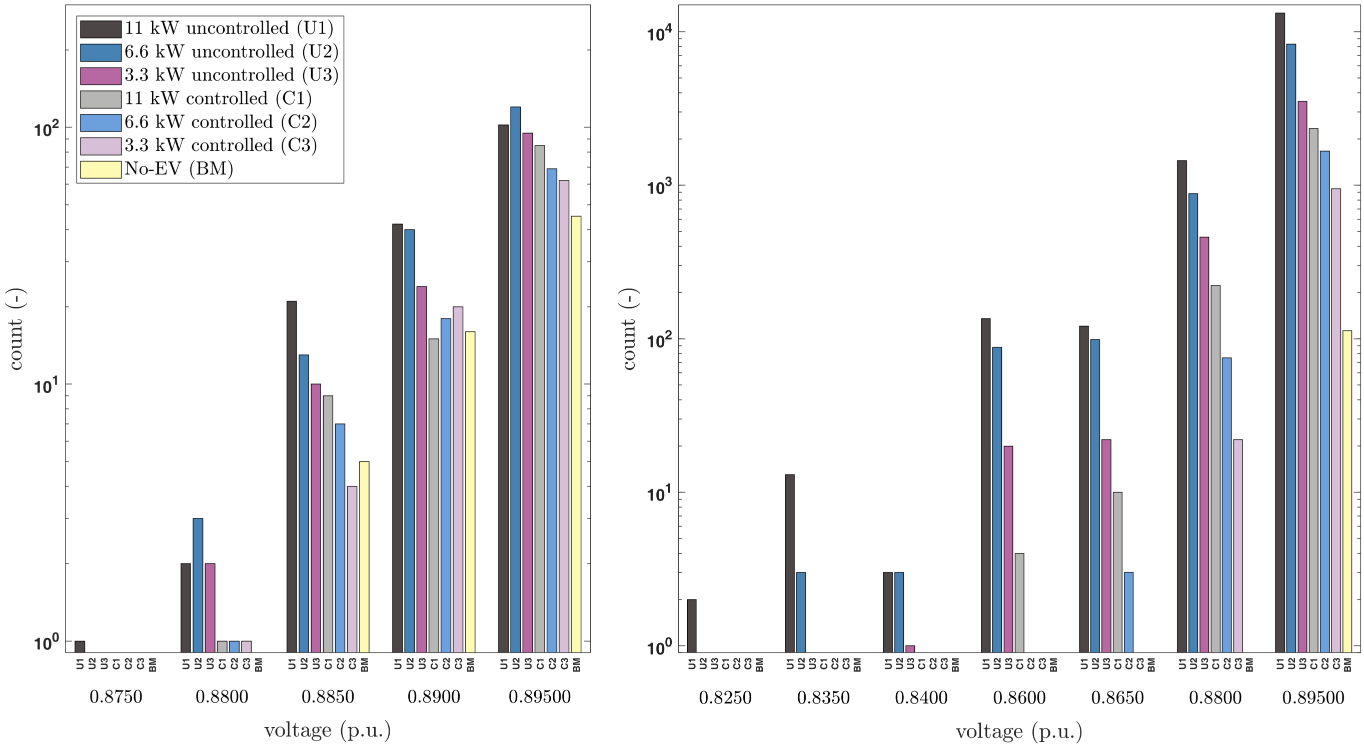

Figure 6. Comparison of the histograms of the voltages below the lower voltage threshold $V_{\text{cri}} = 0.90$ p.u. for the droop controlled EV charging and uncontrolled EV charging for 10% EV penetration (**left**), and 90% EV penetration (**right**).

4. Conclusions

This paper presents a detailed systematic study on the voltage-based droop control method for EV charging to determine its aptitude in view of recent trends in residential charging infrastructure. We evaluated the results using long-term load flow simulations, considering real topological parameters of a residential grid and load profiles. The impact on the grid voltage status was investigated, considering a wide range of EV penetrations and three currently available residential charging power levels focusing particularly on 11 kW charging.

The results indicate that, at low EV charging power levels, the voltage-based droop control method facilitate the compliance with the the voltage magnitude standards defined in ENE50160 for the full range of EV penetrations. For EV penetrations up to 80%, the droop-controller is capable of mitigating the violations even for 11 kW charging ensuring the compliance with the voltage magnitude standards as discussed in previously published literature. However, the grid is not in compliance with the EN50160 standards with a high penetrations of EVs charging at 11 kW charging, as the droop control is not capable of curtailing the voltage deviation such that it is kept above the limit of −15% at all times.

In addition to the grid voltage improvements, the droop controller is also capable of providing peak power reduction at the transformer by over 10% at 100% penetration. In this manner, voltage droop method has the potential to reduce the stress on the distribution transformers. However, the EV users will experience longer charging times most particularly at 11 kW charging as charging rates are reduced by up to 43%. This limitation can be ameliorated by adding local PV production, which can recover the charging droops.

The voltage-based control method is discussed as a relatively inexpensive and easy-to-deploy solution, which only requires the local voltage measurements at the point of connection. However, it is highly necessary to investigate the usability of the method also for upcoming trends in the EV deployment, as the grid planning and investments are intended for long-term. Our results show that the method does not guarantee the safe operating conditions in the grids at high charging power levels and high penetrations. However, it can be concluded that the approach is well suited for the early stages of EV market penetration, and even can provide a solution for high penetration rates, if low nominal EV charging power levels are deployed which would allow DSOs more time until sophisticated methods are available.

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Publication B

Author Contribution

- Literature survey of DSM of EVs
- Formulation of the linear optimization problem for charge scheduling
- Concept of the simulation method
- Implementation of the simulation software in MATLAB and evaluation
- Analysis of the results
- Manuscript preparation

Autonomous Demand Side Management of Electric Vehicles in a Distribution Grid

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***Abstract*—The electricity demand due to the increasing number of EVs presents new challenges for the operation of the electricity network, especially for the distribution grids. The existing grid infrastructure may not be sufficient to meet the new demands imposed by the integration of EVs. Thus, EV charging may possibly lead to reliability and stability issues, especially during the peak demand periods. Demand side management (DSM) is a potential and promising approach for mitigation of the resulting impacts. In this work, we developed an autonomous DSM strategy for optimal charging of EVs to minimize the charging cost and we conducted a simulation study to evaluate the impacts to the grid operation. The proposed approach only requires a one way communicated incentive. Real profiles from an Austrian study on mobility behavior are used to simulate the usage of the EVs. Furthermore, real smart meter data are used to simulate the household base load profiles and a real low voltage grid topology is considered in the load flow simulation. Day-ahead electricity stock market prices are used as the incentive to drive the optimization. The results for the optimum charging strategy is determined and compared to uncontrolled EV charging. The results for the optimum charging strategy show a potential cost saving of about 30.8% compared to uncontrolled EV charging. Although autonomous DSM of EVs achieves a shift of load as pursued, distribution grid operation may be substantially affected by it. We show that in the case of real time price driven operation, voltage drops and elevated peak to average powers result from the coincident charging of vehicles during favourable time slots.**

***Index Terms*—electric vehicles, peak demand, demand side management, unidirectional communication, optimum charging strategy**

NOMENCLATURE

C_{bat}	Battery capacity (kWh)
c	Incentive function (EUR/MWh)
E	Energy content of the battery (kWh)
N	Number of time steps (-)
P_{c}	Nominal charging power (kW)
P_{d}	Power consumed during driving (kW)
SOC	State of charge (%)
SOC_0	Initial state of charge (%)
SOC_{max}	Maximum state of charge (%)
SOC_{min}	Minimum state of charge (%)
u	Switching signal (-)
V_{min}	Minimum voltage (pu)
η_{c}	Charging efficiency (-)
Δt	Time step (s)

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I. INTRODUCTION

Electric vehicles (EVs) are emerging as an attractive alternative to internal combustion vehicles due to the increasing concerns over environmental issues and economic aspects. However, transition towards e-mobility poses new challenges for power grids.

The expected increasing number of EVs connected to power systems for charging will have significant impact on the power system operation, including: 1) transformer overloading; 2) increased line congestion levels; and 3) changes in load profile. Among these, the impact of EV charging load on the system load profile claims most attention [1]. Furthermore, uncoordinated and random charging activities could significantly stress the distribution systems causing severe voltage fluctuations and power quality problems [2].

Enhancements in the existing generation capacity and network assets are required to avoid the negative impacts of EV integration on the grid. However, demand side management (DSM) is considered as a promising approach to mitigate the resulting impacts due to charging of EVs without substantial expansions in the grid.

Most of the DSM approaches for EVs discussed in literature are centralized [2,3]. In the approaches referred to, a central entity determines the charging strategy taking into account information on the EVs (SOC, connectivity, preferred end charging time), the grid (voltage, frequency, power losses, line overloading, peak demand), and the market place (electricity prices). In these approaches, the control signals for EV charging are communicated to the EVs individually. As a result, these approaches require two-way communication between a central controller and EVs as well as large amount of data transfer. Moreover, computational burden on the central controller increases with high penetration levels of EVs.

In contrast, decentralized approaches for EV charge management require less communication infrastructure and the computational burden is distributed among the local controllers. In literature, few decentralized approaches have been proposed. Vay and Anderson [4] propose a decentralized EV charging management approach, which is based on a time of use tariff (TOU). Yet, simple DSM schemes based on TOU are not necessarily beneficial at high vehicle penetrations levels [5]. Another decentralized charging control algorithm for plugin EVs has been proposed by Ma and Callaway [6], where the vehicle charging schedules are computed in situ based on a pricing signal received. This information is communicated to the utility, which in turn updates the pricing signal and communicates it again to the EV. This procedure is done until convergence. Therefore, it needs bi-directional communication infrastructure. Richardson et al. [7] propose and compare a local and a centralized method for the optimal charging of EVs in low voltage grids to maximize the total amount of energy consumed by EVs, while maintaining the network within acceptable operating limits. But they do not evaluate the energy costs and diversity in the vehicle usage is also not considered.

Simple decentralized charging strategies based on real time pricing (RTP) are discussed to reduce the detrimental effects on the operation of the power system from charging of EVs, but they are analyzed insufficiently. Therefore, we investigate a decentralized DSM strategy for EVs, which is based on cost minimization. The main contribution of this paper is to provide a more realistic analysis of a RTP driven decentralized DSM approach and its impact on the distribution grid. The main features of this paper compared to the studies available in literature can be summarized as follows:

- We present an autonomous optimization method for EV charging based on a unidirectional cost function that would only require one-way communication, hence resulting in less communication infrastructure requirements and data processing. The proposed approach aims to obtain the optimal solution to minimize the charging cost of individual vehicles.
- We incorporate real statistical data on driving in the simulation framework.
- We consider real household load profiles instead of synthetic load profiles.
- We analyze the optimum cost savings with respect to the current electricity market prices.
- We evaluate the changes in the performance of the grid under the proposed optimization strategy with different penetration levels of EVs using a load flow of a real distribution grid and consider long-term simulations.

Thereby, this study will provide not only an analysis of the market driven load shift potential, but also quantify the impacts of autonomous RTP driven DSM of EVs on the distribution grid operation.

The paper is structured as follows. Section 2 describes the concept of autonomous DSM for EVs, the EV model, and presents the formulation of the corresponding linear optimization problem. The simulation framework used to test and evaluate the suggested method is described in detail in section 3. The results are presented in section 4, followed by a conclusion in section 5.

II. Approach

A. DSM Concept

The DSM concept proposed in this paper is based on autonomous optimum EV charging with unidirectional communication as illustrated in Fig. 1.

The incentive function is a one way communicated price signal transmitted from a central entity to the DSM devices. The incentive signal received serves as cost function $c(t)$ for the optimizer to determine the charging schedule for the EV. A mathematical model of the EV is used to formulate the problem of charging cost minimization. The switching signal $u(t)$ is determined as the solution of this optimization, taking into account the state of charge (SOC) of the vehicle and the expected driving demand. In this work, perfect knowledge of the vehicle usage is assumed. The optimization problem is formulated such that the energy demand for the next day is fulfilled.

The behaviour of the EV with the switching signal determined by the optimizer is simulated using the EV model in the simulation.

The applicability of the proposed method of DSM has been evaluated for domestic hot water heaters and stationary battery energy storage systems by Kepplinger et al. [8] and Faessler et al. [9].

B. EV Model

In this study, the dynamic behaviour of the EV battery is considered to be linear. The EV model used in the simulations is mathematically expressed by

$$\frac{dE}{dt} = \eta_c \, P_c \, u(t) - P_d(t), \tag{1}$$

where $E(t)$ is the time dependent energy content of the battery. The optimization and the simulation are both based on this linear model.

C. Optimization Problem

The objective of the optimization is to find the charging strategy for each individual EV, which minimizes costs with respect to the incentive. It is assumed that the driving pattern of the user is known in advance. The objective function for

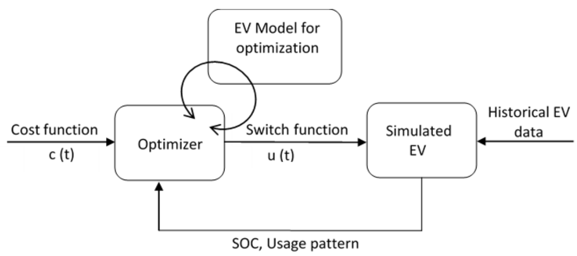

Fig. 1. Concept for autonomous DSM of EVs.

the optimization problem for N time steps can be formulated as follows:

$$\min_{\boldsymbol{u}} \quad \sum_{i=1}^{N} c_i \, u_i \, P_{\mathrm{c}} \, \Delta t \qquad \text{s.t.} \tag{2}$$

$$SOC_{\min} \leq SOC_i \leq SOC_{\max} \quad \forall i, \tag{3}$$

$$0 \leq u_i \leq 1 \quad \text{for } i \text{, where vehicle is at home,} \tag{4}$$

$$0 = u_i \qquad\qquad \text{else.} \tag{5}$$

The optimization is formulated such that it guarantees that the SOC of the battery always remains within the upper and lower operational bounds by the constraint defined in Eq. (3).

The charging rate of the EV is varied in a continuous manner within the upper and lower limits by setting the constraint in Eq. (4).

The constraint defined in Eq. (5) is used to ensure that the charging of the vehicle occurs only when it is connected to the charger at home, thus charging at workplace and public charging is not considered.

The SOC at time step i is calculated by

$$SOC_i = SOC_0 + \frac{1}{C_{\mathrm{bat}}} \Big\{ \sum_{j=1}^{i} u_i \, \eta_{\mathrm{c}} \, P_{\mathrm{c}} \, \Delta t - \sum_{j=1}^{i} P_{\mathrm{d},j} \, \Delta t \Big\}$$

$$\forall i = 1, \ldots, N. \tag{6}$$

where $P_{\mathrm{d},j}$ and SOC_i refer to the discretization of $P_{\mathrm{d}}(t)$ and $SOC(t)$, respectively.

III. Simulation Setup

The optimization for scheduling the charging of the EVs as defined in Eq. (2-5) is implemented using the linear optimization tool available in MATLAB [10] and evaluated in a simulated distribution grid for a total of nine scenarios to reflect increasing EV penetration rates.

The simulation framework used for load flow of distribution grids was implemented in MATLAB [11] based on a direct numerical method as proposed by Ghatak and Mukherjee [12]. The implementation provides interfaces, which allow to test and evaluate the proposed DSM strategy for EVs [13]. In the following section, the data used as input for the simulation study is presented in detail.

A. Distribution Grid Topology

In this study, real data for a weakly meshed low voltage distribution grid in Vorarlberg, Austria is considered. The data for the grid is made available by the local system operator, Vorarlberger Energienetze GmbH [14]. The considered distribution grid comprises 49 nodes including the slack node and is operated at a nominal voltage of 230 V.

B. Household Base Load Curves

The base loads for the households are represented by real smart meter data collected from Vorarlberger Kraftwerke AG (VKW) [15] with a time resolution of 15 minutes. The smart meter data are available for 351 households for the period of 01.04.2016 to 01.09.2016. The household data are assigned to load nodes of the distribution grid randomly using a uniform probability distribution.

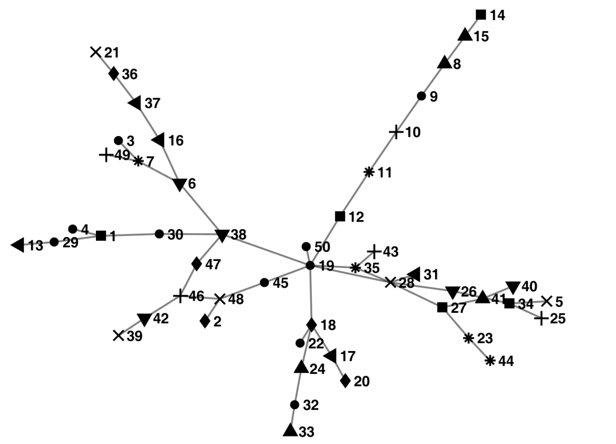

Fig. 2. EV presence at the node for the different scenarios in the distribution grid: ● None ◀ : Scenario 1-8; × : Scenario 2-8; ▼ : Scenario 3-8; ♦ : Scenario 4-8; ∗ : Scenario 5-8; + : Scenario 6-8; ■ : Scenario 7-8; ▲ : Scenario 8

C. EV Parameters

The EV batteries are modelled with a capacity of C_{bat} = 24 kWh and a nominal charging power of P_{c} = 6.6 kW assuming a 230 V single phase connection. The charging efficiency of the EV charger is assumed to be $\eta_{\mathrm{c}} = 90\%$ and the energy consumption efficiency of EV during driving is considered to be 0.15 kWh/km. The minimum SOC of the EV battery is set to $SOC_{\min} = 30\%$ from the nominal value and the maximum SOC is set to $SOC_{\max} = 90\%$.

D. Mobility Profiles

The driving profiles of the EVs are simulated based on the Austrian mobility survey " Österreich unterwegs 2013/2014" [16]. The records in this survey comprise the details of the departure and arrival times of trips and the distance driven in each trip for different vehicle users. These records are used to generate the driving profiles, which include the energy consumption during driving and the availability for charging. With the recorded data, 29,162 driving profiles are created and used for the simulation. It is assumed that the vehicle is available at home before it departs for the first trip and after the last trip of the day. Moreover, the charging is assumed to be occurring only when parked at home, so public charging and charging at work place is not considered.

E. Incentive Function

Day ahead stock market prices from the Austrian electricity market (Energy Exchange Austria EXAA) with a time resolution of 15 minutes are used as the incentive function for the optimization [17]. The prices are available at 12 noon for the next 36 hours. The optimization problem is solved every 24 hours at noon, taking the available prices for the next 36 hours into account.

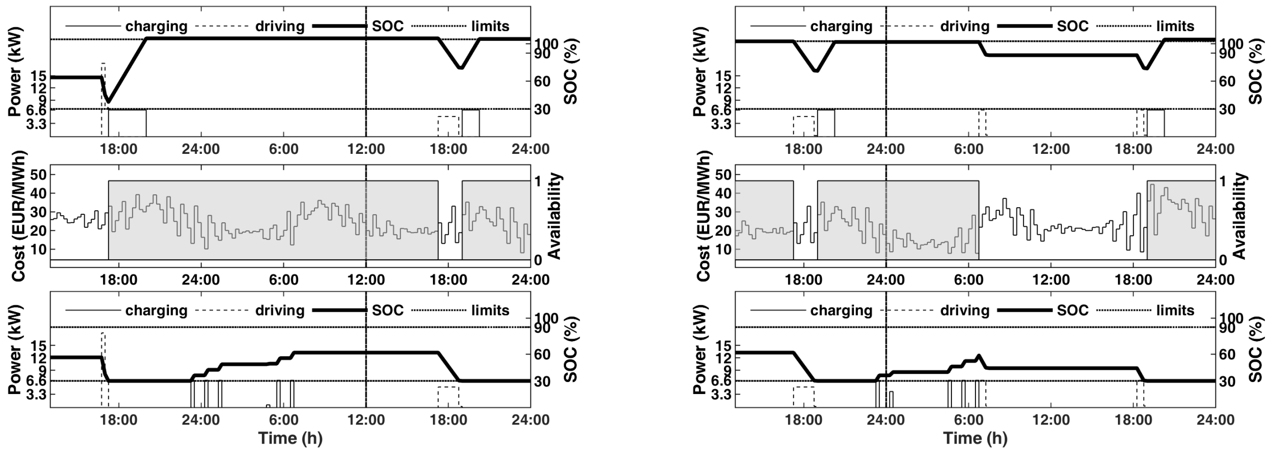

Fig. 3. Two consecutive optimization time windows. The horizontal lines refers to the beginning and ending of the overlapping time window. **Left:** Optimization time window for day 1 **Right:** Optimization time window for day 2. **Top:** Charging rate, power usage during driving, SOC and the SOC limits for uncontrolled charging. **Middle:** The cost function and the availability of the EV for charging. **Bottom:** Charging rate, power usage during driving, SOC and the SOC limits for optimized charging.

F. Simulation Scenarios

The load flow simulation for the distribution grid is conducted for price optimized charging of EVs for eight different scenarios reflecting different penetration rates. In scenario 1, five EVs are connected randomly to the grid nodes and in each successive scenario, five more EVs are added. As a comparative setting, a case with uncoordinated charging of EVs is simulated for all the considered EV penetration rates. In the uncoordinated charging, EVs are allowed to charge at maximum charging rate P_c as soon as they arrive home, until fully charged. In all the simulated scenarios, the same household base load profiles are maintained at all the nodes for both uncontrolled and optimized charging to assure the consistency. Fig. 2 shows the assignment of EVs to the grid nodes for the evaluated scenarios.

As a reference case, a simulation is conducted without the presence of EVs for comparison.

IV. Results

A. Single EV

The charging process of a single vehicle for two consecutive days for both operation modes, uncontrolled and optimized charging, is shown in Fig. 3. The shaded area in the middle plot represents the time periods where the vehicle is available at home and, therefore, available for charging. In the uncontrolled operation mode, the vehicle charges regardless of the incentive, i.e., as soon as it arrives home. In the case of optimized charging, the charging is shifted to low price periods to realize minimum charging cost. Furthermore, the EV is only charged to ensure that the mobility needs for the considered 36 h time window are met. Additionally, the SOC of the EV is kept within the defined minimum and maximum limits. At the beginning of the next optimization time window (12 noon), the optimization is repeated and the charging schedule is adapted considering the latest available stock market prices and mobility needs of the EV user. This overlapping optimization time windows ensures that all information, which is available at the point in time considered, is taken into account for the optimization process.

B. Different EV penetrations

Simulation results for all the simulated scenarios for uncontrolled and price optimized charging are summarized in Table I.

For scenario 1 (10.4% of EV penetration), the cost savings per kWh charging with the proposed price optimization is 30.8%. For the highest penetration rate considered in scenario 8 (83.3% of EV penetration) the cost savings are even higher with 31.6%. Therefore, the proposed method performs reasonably well with low vehicle penetration rates as well as high penetration rates in terms of cost savings.

The results show that optimized charging leads to an average cost saving of 31.1% with respect to the uncoordinated charging.

These results corresponds to an incentive signal based on stock market prices, since a correlation between the demand and the price on the market is a reasonable assumption.

Furthermore, the amount of energy for charging is nearly 4.2% lesser in the case of price optimized charging for all the scenarios.

C. Grid Impacts

Although the proposed method results in reduced charging costs, the overall impact on the grid has to be evaluated in order to examine how it effects grid operation.

The total power variation at the slack node on a single day with 25 EVs connected (52% EV penetration rate), is illustrated in Fig. 4.

TABLE I
SIMULATION RESULTS OVERVIEW FOR THE DIFFERENT SCENARIOS, AS WELL AS UNCONTROLLED (UNC) AND OPTIMIZED (OPT) OPERATION OF EVS.

Scenario	Nr. of EVs	Penetration rate (%)	Total Cost (EUR) Unc	Total Cost (EUR) Opt	Total Energy (kWh) Unc	Total Energy (kWh) Opt	Savings per kWh (%)	PAPR Unc	PAPR Opt	Relative Losses (%) Unc	Relative Losses (%) Opt	$V_{\min}$ (pu) Unc	$V_{\min}$ (pu) Opt
Ref	-	-	-		-		-	2.653		0.785		0.96	
1	5	10.4	136.64	90.37	4835.6	4619.5	30.77	2.545	2.550	0.8632	0.8605	0.95	0.95
2	10	20.8	277.50	183.99	9830.7	9410.8	30.74	2.477	2.976	0.9330	0.9348	0.93	0.93
3	15	31.3	410.33	269.86	14544	13918	31.28	2.457	3.564	1.0083	1.0214	0.93	0.92
4	20	41.7	568.69	376.54	20059	19192	30.80	2.703	4.174	1.0564	1.0840	0.93	0.90
5	25	52.1	701.46	464.36	24801	23757	30.89	2.732	4.754	1.1106	1.1525	0.93	0.89
6	30	62.5	841.10	553.04	29685	28462	31.42	2.875	5.054	1.1691	1.2333	0.93	0.89
7	35	72.9	976.96	641.12	34514	33091	31.55	3.082	5.424	1.2351	1.3219	0.93	0.89
8	40	83.3	1113.40	730.18	39359	37747	31.62	3.592	5.760	1.3021	1.4176	0.92	0.89

The uncontrolled charging of the EVs coincides with the nominal peak demand and even increases it further. In contrast, the price optimized charging shifts the charging load to the low price periods from the nominal peak demand time. However, the aggregated effect of EV charging leads to power spikes at the slack node, which, in turn exacerbate the effects on the distribution grid operation.

In order to evaluate the resulting impacts of the proposed optimization on the distribution grid, the peak to average power ratio (PAPR) at the slack node, the total distribution line losses and the minimum per unit voltage ($V_{\min}$) at the nodes are examined and summarized in Table I.

The results show an increase in PAPR for both operation modes with increasing penetration rates. The increment of PAPR for the optimized charging is higher compared to the uncontrolled charging, as it leads to simultaneous charging of EVs during low cost time periods. Thus, overloading of the transformer during these time periods is more likely.

The minimum voltage in the system is reduced for increasing EV penetration rates for both operation modes. Moreover, for scenarios 4-8, i.e. above 41.7% EV penetration rate, the minimum voltage decreases to 0.89 pu for optimized charging. Hence, these scenarios present challenging impacts for the reliability of the distribution network.

The relative distribution losses increase for higher penetration rates from 0.79% in the reference case up to 1.41% in scenario 8 with optimized charging.

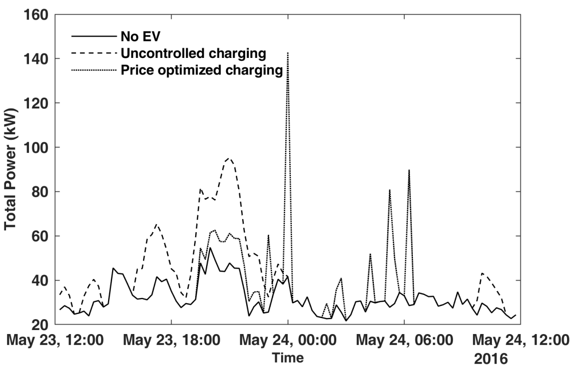

Fig. 4. Total power variation at the slack node with 52% EV penetration rate

V. CONCLUSION

This paper takes up the idea to use real time pricing mechanisms for DSM, as discussed in literature, and applies it to EVs. The impact of both, uncontrolled and autonomously optimized charging of EVs in a real distribution grid topology is investigated. Although the autonomous DSM approach shows a high potential considering the real electricity market data, the negative impact on the grid is even higher as in the case of uncontrolled charging. This can be attributed to the spread of the arrival times, which results in lower simultaneity of EV charging, if plugged in on arrival. This study shows the imperative need of conducting distribution grid simulations to analyze DSM algorithms.

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Publication C

Author Contribution

- Literature analysis of publications in the field of DSM of EVs
- The concept of OPT control architecture
- Implementation of the simulation software in MATLAB and evaluation
- Analysis of the results
- Manuscript preparation

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Research papers

Optimal power tracking for autonomous demand side management of electric vehicles

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ABSTRACT

Increasing electric vehicle penetration leads to undesirable peaks in power if no proper coordination in charging is implemented. We tested the feasibility of electric vehicles acting as flexible demands responding to power signals to minimize the system peaks. The proposed hierarchical autonomous demand side management algorithm is formulated as an optimal power tracking problem. The distribution grid operator determines a power signal for filling the valleys in the non-electric vehicle load profile using the electric vehicle demand flexibility and sends it to all electric vehicle controllers. After receiving the control signal, each electric vehicle controller re-scales it to the expected individual electric vehicle energy demand and determines the optimal charging schedule to track the re-scaled signal. No information concerning the electric vehicles are reported back to the utility, hence the approach can be implemented using unidirectional communication with reduced infrastructural requirements. The achieved results show that the optimal power tracking approach has the potential to eliminate additional peak demands induced by electric vehicle charging and performs comparably to its central implementation. The reduced complexity and computational overhead permits also convenient deployment in practice.

1. Introduction

Transition towards e-mobility poses new challenges for the operation of electricity networks and especially for the distribution grids. The uncoordinated and random charging activities could significantly stress the distribution system causing increased peak demands, severe voltage fluctuations, increased losses, increased transformer and cable ageing, sub-optimal generation dispatch, degraded system efficiency and economy, as well as increasing the likelihood of blackouts due to network overloads [1–4]. These undesirable impacts can be mitigated by proper coordination of EV charging with demand response strategies. Electric vehicle (EV) loads offer high temporal flexibility since they are available for charging over prolonged periods of time. Therefore, the flexibility of the EV demand can be exploited to improve the operation of distribution networks through various load management strategies with the objective to provide valley filling and/or peak shaving services, reduced distribution network losses, reduced ageing of transformers and lines, and increased renewable energy penetration [5,6].

The integrated functions of smart grids in the domains of communication, networking, monitoring and advanced control enable automated energy management systems. These systems result in improved load management and energy efficiency [7]. Decentralized autonomous demand side management (ADSM) is one such management strategy in which the computations are distributed over the respective participating appliances. Scalability due to the reduced dimension of the associated optimization problems permits it to be feasible even at high EV penetration. These features, in conjunction with the reduced communication requirement, render decentralized ADSM a cost-efficient solution for EV charging management compared to the centralized ADSM approaches [8]. In literature, ADSM strategies for EV charging are proposed to reduce the detrimental impacts for the grid operation, many of which have been focused on flattening the load curve. Although the EV scheduling is determined locally, existing approaches often need bi-directional communication between a central entity and the EVs.

Ma et al. [9] propose a decentralized non-cooperative game theoretic approach for the charging management of an infinite homogeneous Plug-in electric vehicle (PEV) population, where the PEVs are coupled

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Nomenclature

ADSM	autonomous demand side management
DSO	distribution system operator
ESS	energy storage system
EV	electric vehicle
LV	low voltage
OPF	optimal power flow
OPT	optimal power tracking
PEV	plug-in electric vehicles
SOC	state of charge
TOU	time of use
C_j^B	battery capacity of the *j*th EV (kWh)
E	total energy requirement of the EVs for a given time frame for driving (kWh)
E_{avg}	average energy consumption of an EV during driving (kWh/km)
E_j	energy requirement of the *j*th EV for the optimization time window (kWh)
$E_{j,s}$	energy requirement of the *j*th EV at time *s* for driving (kWh)
N^{EV}	number of EVs in the grid
N^T	number of time steps
D	aggregated non-EV load profile for a given time frame (kW)
D_t	aggregated base load power at time *t* (kW)
$P_{j,t}$	charging power of the *j*th EV at time *t* (kW)
$P_{j,max}$	charging power of the *j*th EV at time *t* (kW)
$P_{j,\ t}$	maximum charging power of the *j*th EV (kW)
$P_{j,min}$	minimum charging power of the *j*th EV (kW)
R_{max}	maximum driving range of an EV (km)
S_t	broadcasted power signal at time *t* (kW)
S_t^+, S_t^-	positive and negative parts of the broadcasted power signal respectively at time *t* (kW)
$S_{j,\ t}^+$	tracking signal for the *j*th EV at time *t* (kW)
$SOC_{j,\ 0}$	initial SOC of the *j*th EV (%)
$SOC_{j,\ t}$	SOC of the *j*th EV at time *t* (%)
$SOC_{j,\ max}$	maximum SOC of the *j*th EV (%)
$SOC_{j,\ min}$	minimum SOC of the *j*th EV (%)
Z	valley fill level (kW)
Δt	time step (s)
$\eta_{j,c}$	charging efficiency of the *j*th EV

through a common price signal. The method aims to minimize the generation cost through valley filling using the aggregated PEV demand. The utility collects the individual charging schedules of all the EVs and broadcasts the updated total demand (aggregated EV demand and non-EV demand). Each of the EVs determines its optimal charging schedule to minimize the cost and reports back to the utility. A penalty is imposed if the charging schedule of an EV deviates from the average changing schedule of the population. The process is iterated until the charging strategies are in Nash equilibrium.

In contrast, an iterative optimal decentralized protocol to achieve valley filling for both homogeneous and heterogeneous EV fleets is suggested by Gan et al. [10]. The utility determines and broadcasts a control signal (e.g. electricity price) to incentivize the EVs to shift their electricity consumption to the time slots with lower demands. In response, the EVs update their schedules to minimize the total electricity cost and the penalty for deviating from the previous iteration, and report them back to the utility. The utility progressively guides the EVs by altering the control signal in response to the received EV schedules.

Although both the methods in [9,10] achieve the objective of the load valley filling, they suffer from the longer execution times due to the iterative nature.

In contrary, Binetti et al. [11] propose a decentralized non-iterative real-time EV charging strategy to shift the charging to night valleys. The algorithm sequentially determines the charging schedules of each EV taking into account an estimate of the non-EV load for the planning horizon. Each time when an EV connects, it receives the aggregated load profile from the Distribution system operator (DSO). With this information, EV solves an optimization problem locally to achieve valley filling and reports obtained schedule to the DSO. The DSO updates the aggregated load profile with the newly received charging schedule and whenever a new EV connects, the updated aggregated load profile is communicated. Although the method is decentralized and requires limited information exchange, it necessitates a bi-directional communication channel between the grid operator and the EVs. And there exists the risk of forming adverse second peaks if a large number of EVs grid-connect at the same time [12].

A decentralized offline valley filling algorithm for EV charging, solving a joint optimum power flow (OPF)-EV problem is presented by Chen et al. [13]. In addition, the authors also present a decentralized online algorithm that dynamically tracks the valley filling characteristic. In the online algorithm, the utility broadcasts the valley level to all EVs in a given time step, and each EV computes its charging rate locally to track the received valley level and reports its schedule back to the utility. Afterwards, the utility updates the next valley level based on the collected charging schedules. The results indicate that the proposed decentralized online method achieves near optimality. However, the authors consider only a small set of EVs (9 EVs) in the results presented. But at high EV penetrations, the results may not achieve the valley filling due to simultaneity in charging.

Nimalsiri et el. [14] propose a decentralized method for EV charge scheduling by exploiting the notion of water-filling to track a forecasted energy generation profile. The charge profile of each EV is determined one at a time at the plug-in time of the EV. Upon receiving the expected aggregated demand profile and the energy generation profile from the operator, a given EV determines its' charging profile locally to track the generation profile and sends it to the operator. Then the aggregated demand profile is updated with the received charging profile. The simple arithmetic operations applied to the classical water filling algorithm, facilitates easily integration into local controllers.

All these decentralized approaches [9–11,13,14] achieve a flattened load profile through managing EV charging. Although EV scheduling is decentralized, all of these methods require bi-directional communication.

In contrast to the decentralized methods proposed in the literature, we are interested in developing ADSM methods of energy storage systems (ESS) in distribution grids which only require a unidirectional communication channel owing to the advantages of reduced communication infrastructure and computational burden [15,16].

Decentralized approaches based on unidirectionally communicated pricing signals for EV charging management are discussed in the literature, but are analysed insufficiently. Cao et al. [17] propose an intelligent method to control EV charging loads in response to a TOU price in a regulated market to minimize the charging cost. However, they only analyse the mass of energy shifted to the valley periods and do not examine the effects of simultaneous charging for grid operation during valley periods. We investigated the potential of ADSM with pricing signals for EVs charging with electricity market price as the signal communicated in our previous work [18]. The results show that it leads to unfavorable distribution grid operations and tends to form a new peak during the off-peak triggered by the low electricity prices.

Vay and Anderson [19] describe a price-based decentralized approach for the ADSM of EVs. The method aims to determine the time-of-use (TOU) tariff that minimizes the charging cost without overloading the assets. The individual vehicles optimize their charging based on this TOU tariff. Two variants of the proposed approach have been examined: one with a system-wide tariff and the other with different tariffs at different nodes. The decentralized approach with system-wide prices leads to high simultaneity in charging, therefore does not lead to a smooth load profile. Although the decentralized approach with nodal prices results in a load profile close to perfect valley filling, it is problematic to set different prices for different groups of EV customers.

In previous research, we propose that with unidirectional communication, power signals are more efficient than pricing signals for exploiting the demand side flexibility [20]. The objective of this study is to control the demand side flexibility of EV loads using a unidirectionally communicated power signal to achieve a flattened demand curve at the distribution grid level. The main contributions of the paper are listed below.

- We propose an autonomous decentralized, hierarchical algorithm for exploiting EV flexibility. The proposed method achieves valley filling by optimally tracking a power signal. The solution to the tracking problem is formulated as a convex optimization which demands reduced computational overhead and communication contrary to the methods reported. Therefore, it can be easily integrated into an embedded local controller attached to charging infrastructure and is also suitable for high EV penetrations due to its scalability.
- A load flow simulation of a distribution grid is conducted to evaluate the impact of the proposed optimal power tracking (OPT) based ADSM method on the grid operation. Most of the relevant literature analyse the power balance and often lack the investigation of performance indicators in relation to the grid operation. In contrast, we further analysed the performance indices including the grid voltage, line overloading and power losses to provide a better insight into the grid operation.
- The evaluation is performed over a wide range of EV penetrations to demonstrate the impact of the method on grid operation and computational costs for varying EV densities.
- A benchmark centralized solution is provided to evaluate the computational advantages (computational costs and scalability) of the proposed decentralized solution.
- A comparison on the charging rates and the average charging times between the centralized and decentralized solutions is discussed. This illustrates the impact of the ADSM on the EV charging time, so far not reported in literature.

The rest of the paper is organized as follows: In Section 2, we present the formulation of the optimization problem and in Section 3 we show the simulation framework we used including the models of different elements in the grid model. Section 3 includes the results representing the performance indicators used for the comparison followed by the conclusion in Section 5.

2. Approach

In this paper, we proposed an ADSM for EV charging management by tracking a power signal hence referred to as OPT. The solution to the tracking problem is formulated in a decentralized form to enable easy integration to embedded controller at the EV charging infrastructure. The objective of the proposed decentralized ADSM approach is to charge the EVs such that the aggregated non-EV load and the EV charging load profile is flattened as much as possible. We assume that the non-EV loads have no flexibility for demand response and are only interested in the potential of ADSM in EV load. Charging schedules of the EVs are determined to fill the valleys of the non-EV load profile, thereby achieving a load profile as flat as possible. We do not consider V2G within the scope of this study.

We formulate the proposed OPT problem in a two-layer structure and the overall concept is presented in Fig. 1. In the first layer as depicted in Fig. 1(a), the power signal to be tracked is determined by a central entity using two estimates: 1) the forecasted non-EV load profile D 2) the predicted aggregated EV demand E. Forecasting aggregated EV demand can be justified by the multiple methods proposed in the literature, some of which are k-nearest neighbor, pattern sequence algorithms, lazy learning algorithms, auto-regressive integrated moving average methods, modified pattern-based sequence forecasting methods etc. [21]. Short-term aggregated load prediction is realized in the literature using statistical based methods such as linear regression, auto-regressive integrated moving average and seasonal decomposition or artificial intelligence methods such as bio-inspired/evolutionary computational methods, neural networks techniques, support vector regression, machine learning, deep learning, agent-based systems [22].

The solution to the classical water filling problem [23] is used to determine the constant power level (fill level) Z, to optimally allocate the EV charging demand over the time steps of the planning horizon. The fill level Z is obtained by solving,

$$\sum_{t=1}^{N^T} max\{(Z - D_t), 0\}\Delta t = E, \tag{1}$$

for Z. The power signal S_t which is broadcasted to all the EVs is the difference between the non-EV load profile and the valley fill level Z at each time interval, i.e.,

$$S_t = Z - D_t. \tag{2}$$

The second layer of the OPT approach includes the local control mechanism where each local controller attached to EVs firstly determine the positive part S_t^+ and the negative part S_t^- of the received power signal S_t. Then the signal S_j^+ is scaled as given in Fig. 2(b) with the purpose of obtaining the signal to be tracked by the jth EV using a prediction on the required energy demand of the jth EV, i.e.,

$$S_{j,t}^+ = \frac{E_j}{\sum_{t=1}^{N^T} S_t^+ \Delta t} S_t^+. \tag{3}$$

Each EV tracks $S_{j,\,t}^+$ with minimal deviation. Hence, we refer to the approach proposed as Optimal Power Tracking. When individual EVs track the locally scaled global signal, the aggregated effect leads to a flattened global load profile at the transformer. The OPT approach only requires the predicted non-EV load profile D at the transformer and the total aggregated EV demand E at the central entity. The information related to the EV (SOC, availability, arrival and departure times, usage, specifications etc.) is required locally, therefore sensitive EV information is not communicated to a central entity unlike in the other bi-directional based optimization approaches. The predictions of the EV specific information can be realized either using traditional statistical models such as time series method, auto regressive integrated moving average, regression analysis, Kalman filtering etc. or artificial intelligence methods such as artificial neural networks, support vector machines, and deep learning methods [24].

Within the scope of our study, we present the deterministic solution to the scheduling problem assuming the perfect predictions to establish the feasibility of the optimum power tracking based decentralized ADSM method.

2.1. Decentralized OPT based EV charging

Formulating the OPT problem as a quadratic problem is straightforward, but leads to a computationally expensive implementation. Therefore, we propose a formulation as a linear problem which can be easily integrated into a simple embedded hardware attached to EV charging infrastructure.

The charging schedule for the jth EV is determined by solving the L1-Norm, non-linear optimization problem

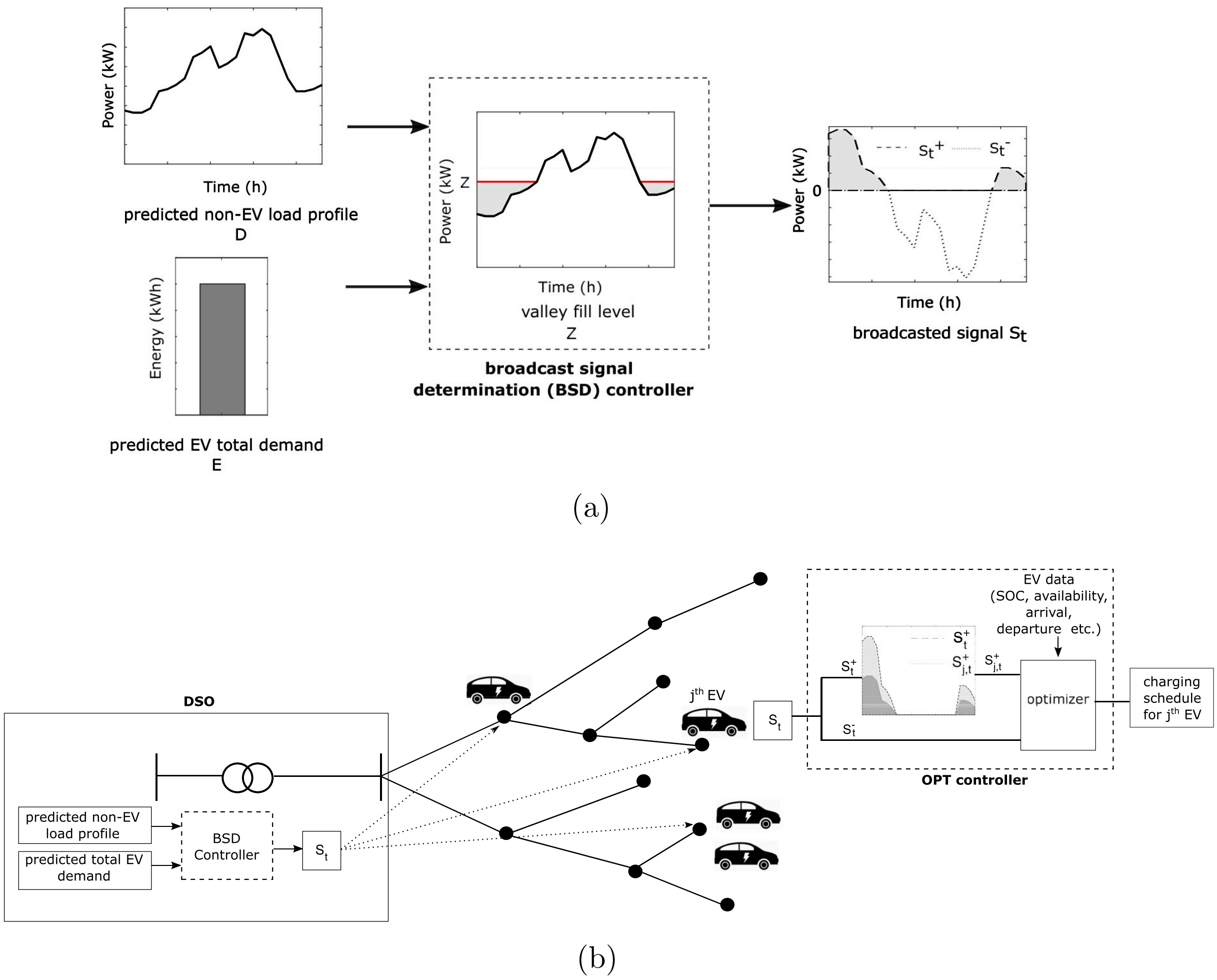


Fig. 1. OPT concept: (a) broadcast signal determination (BSD) controller for determination of the broadcasted power signal using the valley fill level Z based on the predicted non-EV load profile D and the total EV energy demand for the optimization horizon E (b) localized OPT controller for decentralized EV charging scheduling.

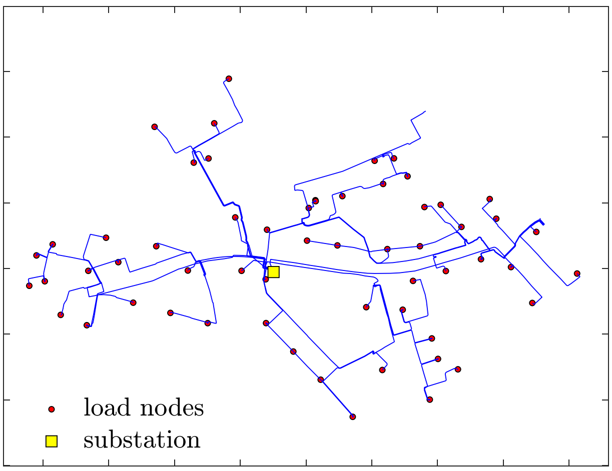


Fig. 2. Low voltage distribution grid.

$$min \sum_{t=1}^{N^{T}} \left(\left| S_{j,t}^{+} - P_{j,t} \right| \left(1 + S_{t}^{-} \right) + \left| P_{j,t+1} - P_{j,t} \right| \right) \Delta t \ \text{ s.t.} \tag{4}$$

$$P_{j,min} \leq P_{j,t} \leq P_{j,max} \quad \forall t, \tag{5}$$

$$SOC_{j,min} \leq SOC_{j,t} \leq SOC_{j,max} \quad \forall t, \tag{6}$$

$$P_{j,t} = 0 \quad \text{for } t \text{, where the EV is not at home.} \tag{7}$$

The charging rate of the EV can be varied continuously within the upper and lower limits given by the constraints (5). Constraints defined in (6) guarantee that the SOC of the EV battery always remains within the upper and lower operational bounds. The constraint defined in (7) is used to ensure that the charging of the EV occurs only when it is available at the point of charging, thus optimization of the charging at public charging infrastructure is not considered. The SOC of the jth EV at time step t is calculated by

$$SOC_{j,t} = SOC_{j,0} + \frac{1}{C_{j}^{B}} \left\{ \sum_{s=1}^{t} \eta_{j,c} P_{j,s} \Delta t - \sum_{s=1}^{t} E_{j,s} \right\}. \tag{8}$$

Note that charging and discharging of a given EV do not occur simultaneously.

The negative part S_t^- of the broadcasted signal S_t is merely used as a weighting factor and serves as a penalty for charging activities during high demand periods of the non-EV load profile. The term $|P_{j,\,t+1} - P_{j,\,t}|$ in (4) is included to avoid high charging rates during deep valley periods. As the aggregated effect might lead to power spikes during deep valley periods, the term penalizes high gradients in charging.

The optimization problem (4) is non-linear in its original form but can be reformulated to an equivalent linear form by adding the auxiliary variables $a_{j,t}$, $b_{j,t}$ rewriting the objective function as in (9), and adding the constraints (10)–(13).

$$min \sum_{t=1}^{N^{T}} \left[a_{j,t}\left(1+S_t^{-}\right)+b_{j,t}\right]\Delta t \quad \text{s.t.} \tag{9}$$

$$-a_{j,t} \leq S_{j,t}^{+} - P_{j,t} \leq a_{j,t} \quad \forall j, \forall t, \tag{10}$$

$$-b_{j,t} \leq P_{j,t+1} - P_{j,t} \leq b_{j,t} \quad \forall j, \forall t, \tag{11}$$

$$a_{j,t} \geq 0 \quad \forall j, \forall t, \tag{12}$$

$$b_{j,t} \geq 0 \quad \forall j, \forall t. \tag{13}$$

2.2. Centralized OPT based EV charging

The centralized implementation of the problem for scheduling EVs to achieve valley filling by tracking a power signal defined in Section 2.1, is performed to provide a comparative assessment to the decentralized implementation. In the centralized solution, the aggregated charging power of all the EVs available for charging should track the power signal S_t^{+}. The objective function of the centralized solution is given by,

$$min \sum_{t=1}^{N^{T}} \left(\left| S_t + - \sum_{j=1}^{N^{EV}} P_{j,t} \right| \left(1+S_t^{-}\right) + \sum_{j=1}^{N^{EV}} P_{j,t+1} - \sum_{j=1}^{N^{EV}} P_{j,t} \left| \right. \right) \Delta t \tag{14}$$

subjected to the constraints (5)–(7).

2.3. Uncontrolled EV charging

As a benchmark, we simulate the uncontrolled EV charging scenario where the EVs start charging at maximum charging rate as soon as they arrive at the point of charging until fully charged. This case gives a general understanding of the effects of increasing EV penetration levels in the distribution grids. It also serves as a benchmark to understand the potential improvements in the distribution grid operation with the proposed OPT algorithm.

3. Case study

Most of the related research in literature having the objective of valley filling focuses only on the power balance and the impact on the peak demand. Other performance indicators related to grid operations such as line load, power losses and voltage drops are equally important, yet often left non-assessed. We performed load flow simulations of a distribution grid in our study to assess these indicators. This section describes the framework including different grid elements which we used for the load flow. The load flow simulation uses the backward forward sweep flow method as proposed by Ghatak and Mukherjee [25]. The simulation tool is implemented in MATLAB® [26] and it serves as an interface to test different optimization algorithms for different demand response devices, in our case EVs [27]. The OPT linear optimization problem is solved using the MATLAB® optimization toolbox. We conducted simulations over a week with a time resolution of 15 min. The selected week was chosen from the winter season as it exhibits a higher demand with respect to other seasons. The optimization problem is solved every 24 h at noon, taking into account the forecasts for the next 36 h. We consider overlapping time windows for the optimization, to ensure that the SOC of the vehicle is always within the limits guaranteeing the energy required for the driving is delivered without failure.

3.1. Distribution grid

Fig. 2 shows the geographical representation of the low voltage (LV) grid located in Austria which is used in this study. The data used to model the grid including information of the distribution transformer, loads (location, load type, annual energy consumption), topology (connectivity, cable type, length), were provided by the local DSO, Vorarlberger Energienetze GmbH [28]. The simulated LV distribution grid comprises a 800 kVA, 10/0.42 kV step down 3-phase transformer with 52 load nodes and 103 distribution lines. The grid supplies 490 residential consumers, 9 business units and 77 other consumer units which include heat pumps, public facilities, etc. Data related to the annual energy consumption for each consumer was also made available by the local DSO. The grid simulation was conducted considering the LV side of the transformer as the slack node with a reference voltage of 1 p.u.

3.2. Non-EV load profiles

The load profiles for the residential consumers were represented by real smart meter data from a field test of the local energy provider illwerke vkw AG (VKW) [29] with a temporal resolution of 15 min. The smart meter data of 351 households over one year was used. A database for the residential power profiles was set after pre-processing the data. Then, the smart meter data were assigned to residential consumers by mapping the annual energy demand. For the non-residential loads, the standard load profiles of the Austrian clearing and settlement agency [30] were used. These standard profiles were scaled according to the annual energy consumption of the particular consumer unit. A power factor of 0.96 was selected.

3.3. EV model

In this study, the dynamic behaviour of the EV battery is considered to be linear as expressed in (8). In modelling the electric vehicle, we used the specifications for the Nissan Leaf as summarized in Table 1.

We assume that the charging infrastructure is equipped with a 3-phase 400V/16 A semi fast charger with a maximum charging power of 11 kW having a charging efficiency ηc of 0.9.

3.4. Mobility profiles

We used the Austrian mobility survey "Österreich unterwegs 2013/2014" [31] to simulate the usage behaviour of the EVs. It contains the travel details of different modes of transport including the arrival and departure time, distance driven, the purpose of the journey and the day of the week. Only the motor vehicles having private related journeys were considered. Statistical filtering techniques were used to remove inconsistencies. The journeys with distances exceeding the maximum range $R_{\max}$ of the selected type of the EV were excluded. The specific energy consumption for a unit time step was calculated using the driving distance and duration, assuming an average energy consumption E_{avg} of 0.15 kWh/km. The generated driving profiles contain the energy consumption of the given vehicle at each time step and the availability at the point of charging. Only the charging of the vehicles at the private charging infrastructure was considered. The difference between weekday and weekend trips was also taken into account in generating the EV

Table 1
EV model specifications.

η_c	0.9
C^B	24 kWh
E_{avg}	0.15 kWh/km
$SOC_{\max}$	90%
$SOC_{\min}$	30%
$R_{\max}$	160 km

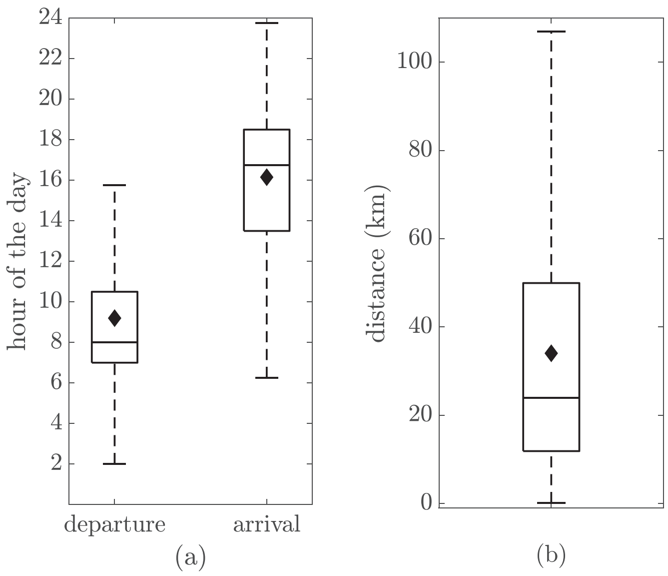


Fig. 3. A summary of the mobility profile statistics representing arrival times, departure times and daily travel distance. (a) The box plots representing the arrival and departure times for the EV profiles used in the simulation. (b) The box plot representing the daily travel distances of the EV profiles used in the simulation.

usage profiles. A total of 15,320 profiles for weekday travels and 6460 profiles weekend travels were generated for the EV user behaviour database. A summary of the mobility profiles including the arrival times, departure times and the daily travelled distances are shown in Fig. 3. The selected mobility profiles have a mean departure time of 09:20 and a mean arrival time of 16:15. The mean distance travelled by a vehicle is 34 km.

We defined the penetration rate as the number of EVs per total number of consumer units. With a penetration rate of 100%, 490 private EVs are considered to be grid-connected. We considered ten different progressively increasing penetrations. The assignment of the EVs to nodes at a given penetration rate was random and EVs were added progressively to maintain consistency. The geographical representation of the locational details for the range of EV penetrations is shown in Fig. A1, in the Appendix A.

4. Results

All the Matlab simulations were run on a server with an Intel(R) Xeon (R) CPU E5-2630 v3 @2.40 GHz processor and 31 Virtual CPUs. Load flow simulations for the considered distribution grid over a week were conducted for ten different EV penetrations (10%–100%, in steps of 10%) for the three scenarios; uncontrolled, centralized OPT and decentralized OPT. In addition, a benchmark case with no EVs is considered which is represented as 0% penetration case. This section includes a comparison of the outcomes for the above three scenarios and the benchmark scenario with no EVS. We used the minimum voltage of the nodes, maximum loading of the lines, total power losses in the lines, peak power at the grid transformer and peak to average power ratio as the indicators to evaluate the impacts on grid operation. As EV penetration increases, the dimension of the state variables in the central OPT becomes very high, making the memory requirements of the optimization problem prohibitive. Given the limited computational capacity, the centralized OPT solution to the scheduling problem is implemented only up to an EV penetration of 40%. A comparison of the execution times for the centralized and decentralized implementations is also presented.

We compared the valley filling capability of the proposed decentralized OPT algorithm against its central implementation. Fig. 4 shows

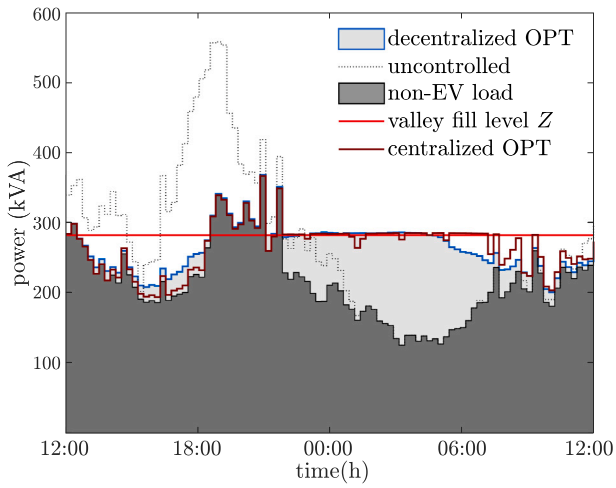


Fig. 4. Power variation at the distribution grid transformer at 40% EV penetration on an example winter day for centralized OPT, decentralized OPT and uncontrolled charging scenarios.

the power profile at the distribution transformer at 40% EV penetration on an example winter day, where the two OPT scenarios and the uncontrolled scenario are compared. In the event of uncontrolled charging, the charging time of the EVs coincides with the peak demand period of the non-EV load profile. Caused by the high simultaneity of the charging events in the uncontrolled scenario, the peak demand in this example case increases from 380 kW to 515 kW. Both the OPT algorithms shift the charging of the EVs to valley hours as they try to follow the reference signal as much as possible. With the decentralized OPT solution, individual EVs track the scaled reference power signal locally, and the aggregated result eventually leads to a flattened load curve. During the daytime and the early morning hours, OPT fails to follow the tracking signal, mostly due to the absence of the EVs at the point of charging. Nevertheless, the constraints defined in the optimization problem always guarantee that the SOC of the EVs remain within the specified limits and fulfil the driving requirements. To benchmark the effectiveness of tracking the reference signal, we computed the mean absolute deviation (MAD) between the valley fill level Z and the total demand

$$MAD = \frac{1}{N^{\mathrm{T}}}\sum_{t=1}^{N^{\mathrm{T}}} |Z_t - \left(D_t + \sum_{j=1}^{N^{\mathrm{EV}}} P_{j,t}\right)|, \tag{15}$$

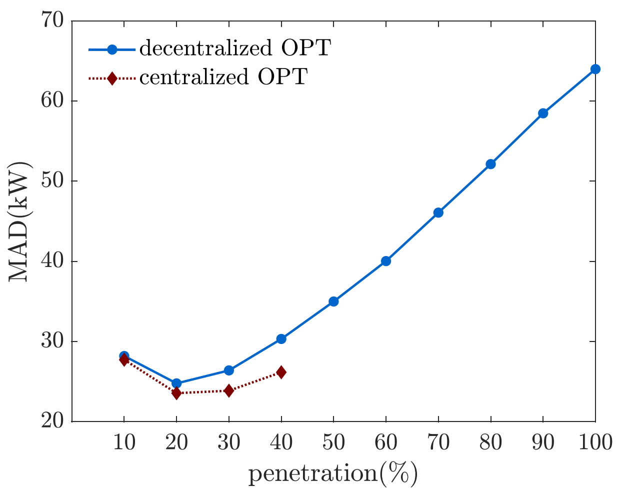
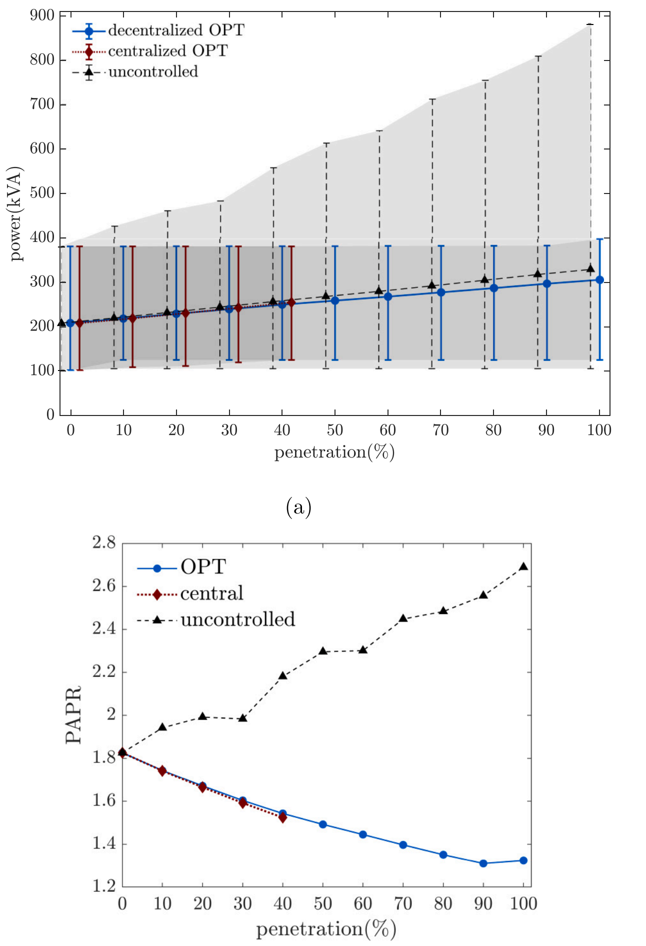


Fig. 5. Mean absolute deviation between the valley fill level Z and the total demand for the centralized and decentralized OPT scenarios.

for the centralized and decentralized OPT scenarios which are shown in Fig. 5. As depicted in Fig. 5, the centralized OPT performs better in realizing the objective of tracking the reference power signal. However, the insignificant discrepancy between the two confirms that the decentralized OPT even with less information exchange is capable of yielding a comparable result to the centralized OPT, offering a compelling alternative to centralized OPT.

To provide a more concise summary of the results, we compare the impact of the two OPT algorithms on the aggregated demand profile for the different penetrations considered in Fig. 6(a). The peak load in the uncontrolled scenario increases with increasing penetration and exceeds the rated capacity of the transformer at an EV penetration of 90%. The peak load in both the OPT scenarios always stays well below the transformer capacity and remains almost the same for all the penetrations considered. OPT achieves this by avoiding EV charging during peak hours and by regulating the charging rates during the valley hours to stay below the valley fill level Z. In this manner, both OPT scenarios are capable of reducing the stress on the distribution grid transformers that could be caused by random charging. Most interestingly, decentralized OPT solution with lower computation complexity is also capable of realizing comparable results as the centralized solution at all the EV penetration ranges. These results are also reflected in the peak to average power ratio(PAPR) as depicted in Fig. 6(b).



(a)

(b)

Fig. 6. (a) Bar chart indicating peak, mean and the minimum power at the distribution grid transformer for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season. (b) The peak to average power ratio (PAPR) for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season.

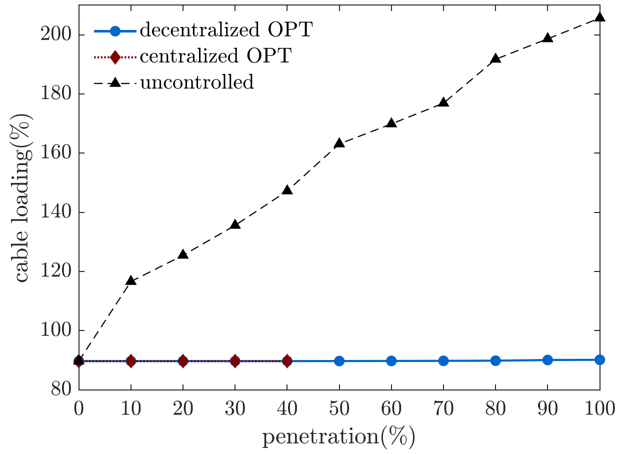


Fig. 7. Maximum resulting cable loading of the distribution cables for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season.

Uncontrolled charging can lead to high current flows in the distribution cables and may even exceed their rated current limits. To assess the impact of different scenarios considered towards the current flow of the cables, we analysed the degree of the loading on the cables; defined as the percentage ratio between the current flow and the rated current of a cable. Fig. 7 shows the comparison on the maximum loading of the grid cables over a week for the three scenarios at different penetrations. The cable loading exceeds the permissible limits even at 10% penetration in case of uncontrolled charging. However, with both OPT scenarios, the observed maximum cable loading remains the same and does not exceed the permissible limits even at high penetrations. Therefore, OPT supports the integration of EVs into distribution grids and reduces the requirement of cable enhancements. Table 2 provides an overview related to the number of cables exceeding the rated capacity in the simulated week for the uncontrolled charging scenario. For both OPT scenarios, no violations in the cable overloading are observed over all the penetrations.

Compliance of the permissible voltage ranges specified in the standards such as ANSI C84.1 is a mandatory requirement for the operation of the distribution grids. The uncontrolled charging can lead to unacceptable voltage drops and cause violation of the specified standards. As shown in Fig. 8, at penetrations above 80%, the minimum voltage of the grid nodes over the simulated week falls below 0.9 p.u. and cause violation in the voltage standards. In OPT scenarios, the minimum nodal voltages do not fall below the standard limits even at high EV penetrations. Therefore it is evident that OPT not only mitigates the peak power problems but also any probable voltage quality problems. A summary of the voltage violations in the uncontrolled scenario is given in Table 2.

Fig. 9 presents the total power losses in the distribution cables over the selected week. The OPT scenarios result in lower total power losses

Table 2
Voltage violations and line overloading for uncontrolled charging, eliminated in OPT scenarios.

Penetration	$N^{\mathrm{Nodes}}_{V<0.9}$	$N^{\mathrm{Lines}}_{\mathrm{loading}>100\,\%}$
10	–	2
20	–	2
30	–	2
40	–	5
50	–	8
60	–	8
70	–	8
80	–	10
90	2	10
100	3	13

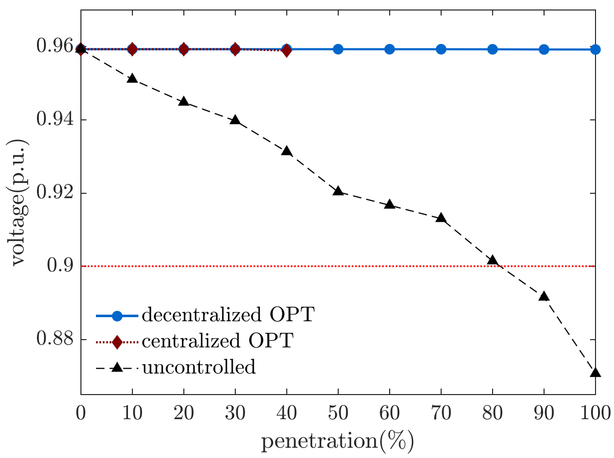


Fig. 8. Minimum nodal voltage in the distribution grid transformer for the decentralized OPT, centralized OPT and uncontrolled charging scenarios for a period of a week in winter season. The dotted straight line represents the lower tolerance boundary of voltage.

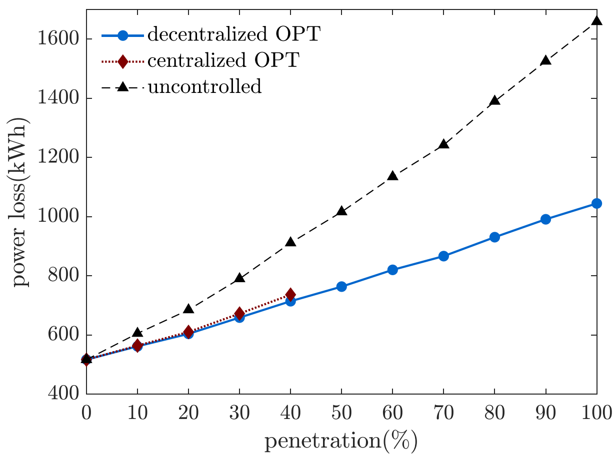


Fig. 9. Total power losses in the distribution cables for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season.

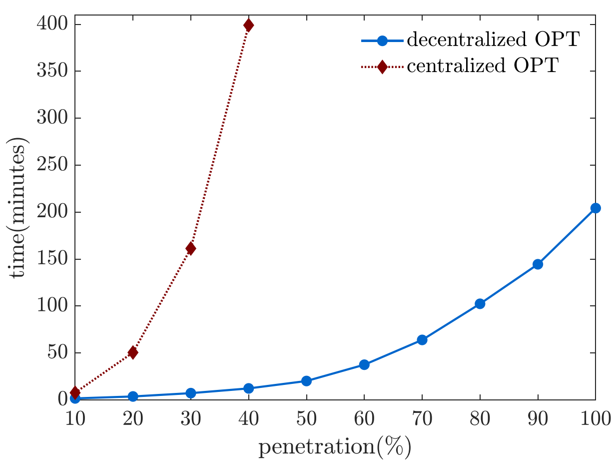
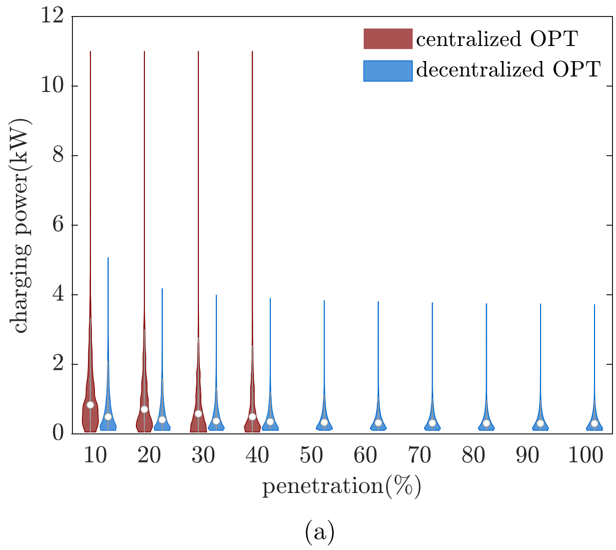


Fig. 10. Computational costs to solve the load management problem for the decentralized OPT and centralized OPT scenarios for a period of a week.

compared to the uncontrolled scenario due to the distribution of the charging events over time which in turn leads to distribution of currents over time. At 100% penetration, the decentralize OPT limits power losses nearly to half from that of the uncontrolled scenario. As such OPT also contribute to improve the efficiency of the grid operation.

The key indicators presented above concerning the grid operation, clearly indicate that the decentralized method performs as good as the centralized equivalent, despite the reduced information exchange. Furthermore, the execution time between the two methods exhibits a clear difference as depicted in Fig. 10. As can be seen in the plot, even at 40% penetration the simulation time for the centralized implementation is around 400 min. The memory requirement for the optimization of the central OPT is very high due to the increasing number of state variables at high penetrations making it debatable for practical implementations. In our simulation, the optimization of the individual EVs are performed sequentially, but in practice this process will be performed in parallel. Hence, the simulation time will be even lower than the values indicated in Fig. 10.



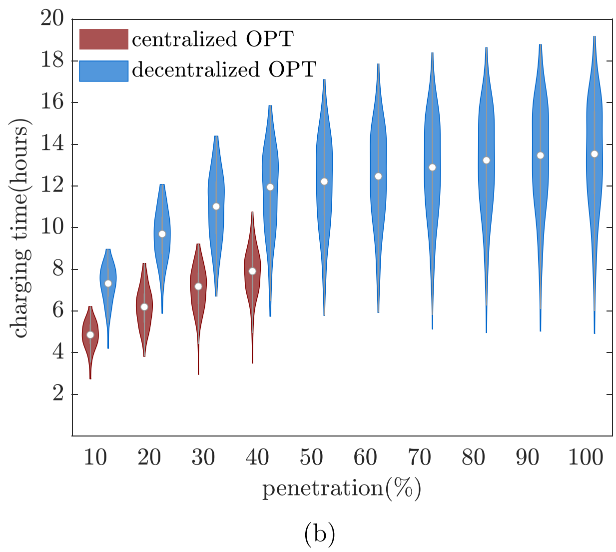


Fig. 11. Comparison of the charging rate and the average charging time between the centralized and decentralized OPT implementations over the range of penetrations (a) charging rate for the decentralized OPT and centralized OPT scenarios for a period of a week. (b) Average charging time per day for the decentralized OPT and centralized OPT scenarios for a period of a week.

Fig. 11 shows a comparison of the charging rates and the average charging time per day over the simulated week for the centralized and decentralized OPT implementations over the range of penetrations considered. The charging rate of the decentralized implementation is lower compared to that of the centralized implementation. This is attributed to the loss of global information on the EV data in the decentralized implementation. Consequently, average charging time is higher in the decentralized OPT compared to central OPT as can be seen in Fig. 11(b). Despite the lower charging rates, the decentralized OPT complies with the demanded energy delivery to all the EVs as in the decentralized OPT.

The results reveal that the uncontrolled charging of EVs leads to increased peak demands, voltage violations, cable overloading and higher power losses, hindering the healthy operation of the distribution grids. Both the centralized and decentralized OPT algorithms improve the distribution grid operation by reducing the peak demand. In addition, these two methods reduce power losses and eliminate voltage violations and cable overloading. Furthermore, the decentralized OPT with local controllers performs equally well as the central OPT. The reduced execution time together with the reduced computational load makes the decentralized OPT a more viable load management strategy especially for high EV penetrations expected in future mobility systems.

5. Conclusions

We proposed a decentralized hierarchical ADSM algorithm for the charging management of EVs where the communication requirement is only unidirectional. We formulated the charging scheduling problem as an optimal power tracking algorithm that aims to reduce the peak demand in distribution grids induced by EV charging. In the first layer, the power signal to be broadcasted is determined using only two predictions: the aggregated time-varying non-EV load profile and the total EV demand in the grid. Then in the second layer, the individual EV controllers solve a localized optimization to realize the charging schedule by optimally tracking the re-scaled broadcasted power signal. Predictions on the individual EV usage behaviour based on historic data are required locally for the scaling and tracking algorithm. We used deterministic non-EV load profiles and EV energy demands in our implementation. The effect of uncertainties related to the predictions will be considered in future implementations. We included a central implementation as a benchmark for comparison purposes.

The results demonstrate that the decentralized OPT approach eliminates the additional peak demand increments induced by EV charging and performs comparably to the centralized OPT implementation. In addition to the peak reduction, benefits also include the reduction of the power losses in the cables as well as prevention of voltage limit violations and cable overloading. A further intriguing feature of the OPT is the reduced computational overhead that makes it well suited for integrating into local embedded controllers attached to existing charging infrastructure. Despite the fact that the decentralized OPT, in contrast to the centralized OPT, leads to longer charging times due to the loss of information on the full extent of the EV data, it ensures the demanded energy delivery to all the EVs. In light of all these facts, is evident that the method is a compelling strategy for grid friendly integration of EVs with no requirement for bidirectional communication and computationally intensive infrastructure in comparison to the centralized methods.

CRediT authorship contribution statement

Muhandiram Arachchige Subodha Tharangi Ireshika: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Klaus Rheinberger:** Conceptualization, Methodology, Writing – review & editing. **Ruben Lliuyacc-Blas:** Data curation, Writing – review & editing. **Mohan Lal Kolhe:** Writing – review & editing. **Markus Preißinger:** Writing – review & editing. **Peter Kepplinger:** Investigation, Resources, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. EV locations

The heatmaps illustrating the number of EVs connected to the nodes at the grid for the different penetrations considered are shown in Fig. A1. The EVs were assigned to the nodes based on the number of households at each node. As can be seen in the Fig. A1(j), the nodes with high EV numbers are distributed over the grid. Even though most EVs are connected at the end of the feeders, the performance indices lie within the safe operating bounds for all configurations.

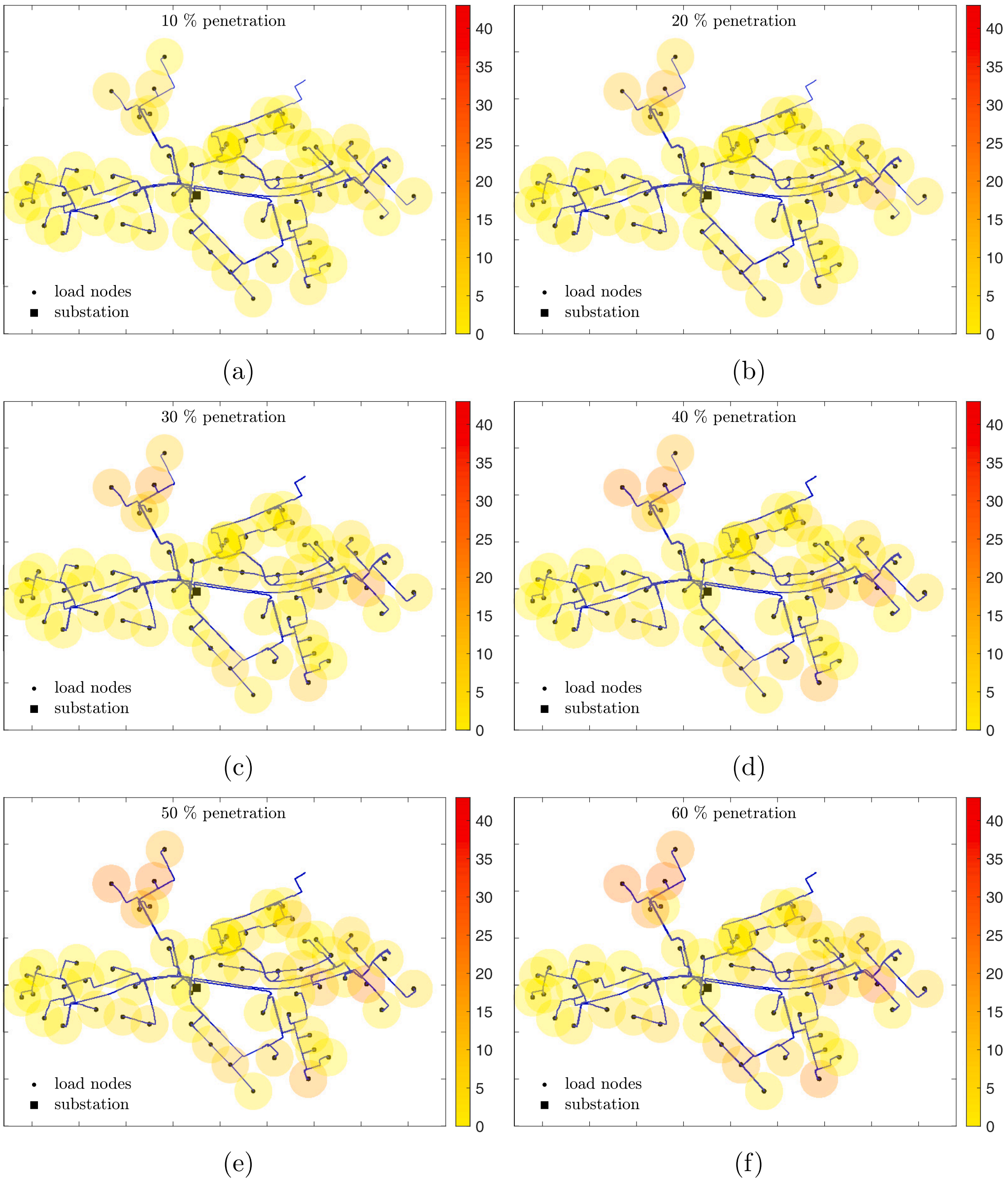

Fig. A1. Geographical representation of locational details for the different EV penetrations in the Austrian low voltage grid. The heatmap represents the number of EVs at each node at the respective EV penetration. The allocation of the EVs is based on the number of households at each node.

Appendix B. Summary of the results

A summary of the results including all the key indices we used for the evaluation and the details of the EV assignments to the different nodes for the range of penetrations is presented in Table B.1.

Table B.1
The summary of the assignation details of EV to network nodes and the results representing key performance indices for the different EV penetrations.

Penetration	No of EVs	No. of nodes with EVs	PAPR			Minimum Voltage (p.u.)			Maximum Line loading (%)			Power Loss (kWh)			Charging Time (hours)		
			Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D
0	0	0	1.83			0.96			89.7			517			0.72		
10	49	23	1.94	1.74	1.74	0.95	0.96	0.96	116.6	89.7	89.7	605	564	562	0.74	4.65	7.28
20	98	30	1.99	1.67	1.67	0.94	0.96	0.96	125.5	89.7	89.7	685	610	604	0.75	6.17	9.64
30	148	35	1.98	1.59	1.60	0.94	0.96	0.96	135.6	89.7	89.7	790	672	659	0.74	7.06	10.95
40	196	35	2.18	1.52	1.54	0.93	0.96	0.96	147.2	89.7	89.7	911	736	714	0.75	7.86	11.72
50	245	40	2.30		1.49	0.92		0.96	163.1		89.7	1016		763	0.74		12.10
60	293	45	2.30		1.45	0.92		0.96	169.9		89.8	1135		820	0.74		12.46

(continued on next page)

Table B.1 (*continued*)

Penetration	No of EVs	No. of nodes with EVs	PAPR			Minimum Voltage (p.u.)			Maximum Line loading (%)			Power Loss (kWh)			Charging Time (hours)		
			Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D
70	342	47	2.45		1.40	0.91		0.96	176.1		89.8	1242		867	0.74		12.79
80	392	48	2.48		1.35	0.90		0.96	191.7		89.9	1390		931	0.74		13.09
90	441	49	2.56		1.31	0.89		0.96	198.6		90.1	1526		991	0.74		13.34
100	490	52	2.69		1.32	0.87		0.96	205.7		90.2	1659		1045	0.74		13.40

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Publication D

Author Contribution

- Literature analysis of publications in the field of DSM of EVs
- Formulation of the MILP optimization and extended methods
- Implementation of the simulation software in MATLAB and evaluation
- Analysis of the results
- Manuscript preparation

IEC 61851 COMPLIANT DEMAND SIDE MANAGEMENT ALGORITHM FOR ELECTRIC VEHICLE CHARGING: A MILP BASED DECENTRALIZED APPROACH

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Abstract

Charging scheduling algorithms play a vital role in diminishing the negative consequences on electricity networks from the widespread adaptation of electro-mobility. Therefore, there is a growing interest in a pragmatic solution that requires only modest resources. To reach this goal, we propose a decentralized, IEC charging standard compliant, two-layer charging scheduling algorithm, which only requires unidirectional communication and reduced computing capabilities. The objective of the algorithm proposed is to achieve valley filling by exploiting the flexibility of electric vehicles through optimal tracking of a target signal. The IEC standard compliant, semi-continuous charging characteristic is attained with a mixed-integer linear formulation. Different formulations of the problem by forming vehicle groups and randomization in charging events are examined. The results show that the IEC 61851-compliant formulation with a semi-continuous charging characteristic for the proposed method fails to perform as good as the variable charging rate formulation, which has a 2.8 and 3.9-fold deviation in the variance of the total demand relative to the variable charging rate at 50% and 100% penetration rates, respectively. Nevertheless, the inclusion of randomization and grouping improves the performance of the IEC standard-compliant formulation. Considering four groups, the variance in demand of semi-continuous charging formulation at 50% penetration is nearly equal to that of the variable charging rate proofing the viable potential of the technically feasible solution proposed.

1 Introduction

The increasing trend towards electrification of the transportation sector has raised a series of technical problems affecting the healthy operation of the electricity network. A number of studies have already highlighted such negative consequences [1–4]. To reduce the impacts of the widespread integration of electro-mobility on the distribution grids, control strategies for electric vehicle (EV) charging are crucial.

A wide range of such demand side management strategies, which exploit the temporal flexibility of the EVs, are discussed in the literature demonstrating a strong potential [5–10]. These studies employ distinct control architectures and methodologies for the charging scheduling process. The majority of the charging schemes proposed employ a variable charge rate, considering that the EV can withdraw power at any rate between zero and a given maximum rate. However, the IEC 61851 standard specifies that beyond the standby mode, the charging current has to be in the range from 6 A to 48 A, being then a semi-continuous variable [11]. Therefore, the studies with variable charge rates, do not meet compliance with the standard IEC 61851. Due to the limitations of the charging technology, the economic and practical deployment of the proposed strategies are therefore debatable.

In a previous study, we proposed an autonomous decentralized demand side management (ADSM) algorithm for EV charging scheduling to flatten the aggregated demand at the low voltage (LV) distribution transformer [12]. The proposed control architecture can be easily deployed by means of a simple embedded controller attached to the EV supply equipment (EVSE) owing to the linear formulation of the optimization. The method also only relies on unidirectional communication and therefore requires few communication resources. These features render it well suited for practical implementations. Similar to the works in [5–9], a variable charging rate, which is not in accordance with IEC charging standards, was assumed, in our previous implementation [12]. Hence in this paper, we aim to adapt this control architecture to comply with charging limits specified in the standards. To meet the requirement defined in the standards, a semi-continuous charging rate is used, which is either zero or varies between the minimum and maximum values. The semi-continuous charging characteristic is realized using a mixed integer linear programming (MILP) formulation.

The aim of the study proposed is to provide an exemplary case that demonstrates the impacts of compliance with standards in control algorithms of EV charging upon the intended outcomes and establish a simple, practically viable control algorithm for EV charging scheduling.

The rest of the paper is arranged as follows. A detailed description of the MILP formulation for the decentralized ADSM method proposed is presented in Section 2. Section 3 includes the simulation setup that we used for the analysis. The simulation results are presented in Section 4 followed by a conclusion in Section 5.

2 Method

The decentralized hierarchical ADSM approach proposed in our previous study is referred to as Optimal Power Tracking (OPT) [12], since the fundamental principle is to track a predefined reference power signal with minimal deviations. The tracking signal is determined to achieve valley filling by exploiting the flexibility of EV demand. The algorithm is formulated in a two-layer architecture as presented in Figure 1. In the first layer, the DSO determines a target power signal S based on the estimates of non-elastic power demand D^* and aggregated total EV demand E^* and broadcasts to all the EVs. In the second layer, with the knowledge of EV user behaviour estimates (arrival times $t_{j,\mathrm{arri}}$, departure times $t_{j,\mathrm{dep}}$, energy demand E_j^*), each EVSE scales the received signal to the expected day ahead EV energy demand and performs an optimization to track the scaled signal with minimal deviations.

2.1 Determination of the target signal

The tracking signal is determined based on the estimated day ahead aggregated non-EV demand profile (D^*) and the estimated total EV energy demand of all the grid-connected EVs (E^*). The day-ahead prediction of the non-elastic load profile is realizable through forecasting tools, in particular, AI-based techniques that are capable of learning complex nonlinear relationships from the historic data [13]. The recent developments in substations equipped with intelligent transformers facilitate the measured load demands [14]. Sub-metering systems offer the possibility to measure the historical EV demand data which can be used to decouple the EV demand to obtain the non-elastic demand. The estimation of the aggregated EV flexibility in the form of a total energy demand value is also achievable with AI-based techniques [15].

The first step to determine the target signal is to obtain the fill level Z by solving,

$$\sum_{t=1}^{N^{\mathrm{T}}} \max\{(Z - D_t^*), 0\}\ \Delta t = E^*, \tag{1}$$

for Z using the two estimates in accordance with the classical water filling algorithm [16]. N^{T} is the total number of time steps of length Δt in the optimization window. The mismatch between the fill level and the estimated non-elastic load profile at each time interval for the optimization horizon S_t is computed and transmitted to the EVs:

$$S_t = Z - D_t^*. \tag{2}$$

2.2 Local optimization at the EVSE with MILP

In the second layer of the OPT, a local optimization is performed by each EV controller. The local controller attached to the EVSE, splits the negative S_t^- and positive S_t^+ parts of the original power signal received S_t. Thereafter, the tracking signal to be optimally tracked is determined using the estimated next-day EV demand for each EV. The tracking signal for the j^{th} EV,

$$S_{j,t}^+ = \frac{E_j^*}{\sum_{t=1}^{N^T} S_t^+\ \Delta t} S_t^+ \tag{3}$$

is derived by scaling S_t^+ to the estimated next day energy demand for the j^{th} EV, E_j^*. The optimization problem is devised to track the S_t^+ with minimal deviation given the EV user behaviour predictions. Methods for EV user behaviour predictions based on clustering [17], data-learning [18], data-driven [19], etc. are discussed in the literature. We proposed a linear formulation in [12] to the optimization problem stated, which demands reduced computational cost. However, as already stated above, the previous implementation assumes a variable charging rate. To meet compliance with the limits specified by the IEC 61851 standards, we re-formulated the original, linear optimization in a MILP formulation. The objective and the associated constraints of the optimization problem

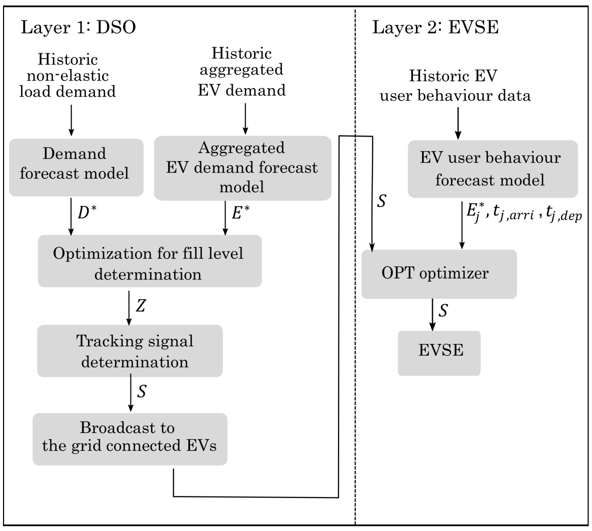

Fig. 1 The two-layer architecture of the optimal power tracking demand side management algorithm for EV charging.

are listed below, where j refers to the j^{th} EV.

$$\min \sum_{t=1}^{N^{\mathrm{T}}} \left[a_{j,t}(1+S_t^-)+b_{j,t}\right]\Delta t \qquad \text{s.t.} \tag{4}$$

$$-a_{j,t} \le S_{j,t}^+ - P_{j,t} \le a_{j,t} \qquad \forall t, \forall j, \tag{5}$$

$$-b_{j,t} \le P_{j,t+1} - P_{j,t} \le b_{j,t} \qquad \forall t, \forall j, \tag{6}$$

$$SOC_{j,\text{min}} \le SOC_{j,t} \le SOC_{j,\text{max}} \qquad \forall t, \forall j, \tag{7}$$

$$x_{j,t}P_{j,\text{min}} \le P_{j,t} \le x_{j,t}P_{j,\text{max}} \qquad \forall t, \forall j, \tag{8}$$

$$x_{j,t} \in [0,1] \qquad \forall t, \forall j, \tag{9}$$

$$b_{j,t} \ge 0 \qquad \forall t, \forall j, \tag{10}$$

$$x_{j,t} = 0 \qquad \forall j, \text{for } t, \text{where the EV is not at home.} \tag{11}$$

Here, $a_{j,t}$ and $b_{j,t}$ are two sets of auxiliary variables, $SOC_{j,\text{min}}$ and $SOC_{j,\text{max}}$ are the minimum and maximum permissible state of charge of the battery of EV_j, specified by the manufacturers. The SOC of vehicle j at time step t is derived assuming a linear battery dynamics:

$$SOC_{j,t} = SOC_{j,0} + \frac{1}{C_j^{\mathrm{B}}}\left\{\sum_{s=1}^{t} \eta_{j,\mathrm{c}}\, P_{j,s}\,\Delta t - \sum_{s=1}^{t} E_{j,s}\right\} \tag{12}$$

where, $E_{j,t}$ refers to the energy demand for driving. $P_{j,t}$ is the charging power of the EV_j at time t. $P_{j,\text{min}}$ and $P_{j,\text{max}}$ are the minimum and maximum permissible charging power of the battery either defined by the EVSE or EV manufacturer. $x_{j,t}$ is a binary variable, which for each EV at time t specifies charging (1) or not-charging (0). It is used to implement the semi-continuous charging characteristics in compliance with the IEC standards for each EV_j at time t.

2.3 *Randomization and grouping*

The limits imposed on the minimum charging current can result in new peaks due to simultaneity, especially at high penetrations. To mitigate this drawback, a randomization and a grouping mechanism are used in the decentralized controllers.

A grouping mechanism, implemented by the DSO, randomly assigns each EV to one of the N_g groups. A new target signal for each group $S_{g,t}$ is derived by segmenting the original target signal S_t into N_g signals, each exhibiting the same time integral reflecting energy. A given EV will receive the target signal created for the group and the total number of EVs present in the group ($N_{\text{EV},g}$). Subsequently, the EVs perform the MILP optimization described in the previous section alongside a randomization process.

In the randomization process, each controller generates a random probability for every time slot of the target signal using a uniform distribution. Only if the probability is higher than a threshold value, charging is allowed. The threshold probability $P_{\mathrm{T},t}$ at time step t is determined based on the percentage of EVs in the group able to charge simultaneously at the minimum charge rate without exceeding the target signal:

$$P_{\mathrm{T},t} = 1 - \left(\frac{S_{g,t}^+}{P_{\text{min}} N_{\text{EV},g}}\right) \tag{13}$$

The performance of the method is highly dependent on the number of groups. Hence, we evaluate and compare the results for different numbers of groups.

3 Simulation Setup

In our study, we conducted load flow simulations of a distribution grid to assess different performance indicators. The load flow simulation [20] implemented in MATLAB® [21] uses the backward forward sweep flow method [22] which is equally applicable for both radial and weakly meshed grids as proposed by Ghatak and Mukherjee. The OPT linear optimization problem is solved using the MATLAB® implementation of cutting plane and branch and bound algorithms. We conducted simulations over a week with a time resolution of 15 minutes. The selected week was chosen from the winter season as it exhibits a higher demand compared to other seasons. The optimization problem is solved every 24 hours at noon, taking into account the forecasts for the next 36 hours. We consider overlapping time windows for the optimization to ensure that the SOC of the vehicle is always within the limits, guaranteeing the energy required for driving is delivered without failure. The simulations are performed under the assumption of perfect predictions of the uncertain parameters since the scope of the study is to evaluate the feasibility of the proposed concept.

3.1 *Grid simulation model*

The topological data of a LV grid in Austria was used as the test grid in this study. The data used to model the grid including information on the distribution transformer, loads (location, load type, annual energy consumption), and topology (connectivity, cable type, length) were provided by the local DSO, Vorarlberger Energienetze GmbH [23]. The simulated LV distribution grid comprises a 800 kVA, $10/0.42$ kV step-down, 3-phase transformer with 52 load nodes and 103 distribution lines. The grid supplies 490 residential consumers, 9 business units, and 77 other consumer units including heat pumps, public facilities, etc. Data related to the annual energy consumption for each consumer was also made available by the local DSO. The grid simulation was conducted considering the LV side of the transformer as the slack node with a reference voltage of 1 p.u.

3.2 *Household load demand*

For the non-elastic household demand data, the Irish Commission for Energy Regulation (CER) dataset from a smart metering project was used [24]. These data having a half-hour sampling time were re-sampled to a sampling interval of 15 minutes. After filtering the incomplete data, a data set of 4225 customers was considered. The household demand data spans over a year from 14th July, 2009 to 31st December, 2010.

3.3 EV load demand data

The historical residential charging data were obtained from records of the experimental statistics of the Electric Charging Point Analysis project funded by the Office of Low Emission Vehicles [25]. The records include charging events spanning over a year for residential charge points in the UK. The data contains time-stamp data that determines the corresponding time of connection (start time of charging session), the time of the disconnection (end time of charging session), the amount of energy supplied, and the charging rate for each identified charging session. To demonstrate the feasibility of the concept, a perfect prediction of EV usage behaviour was assumed.

3.4 EV specifications

In modeling the electric vehicle, we used the specifications of the Nissan Leaf with a battery capacity of $C_j^{\mathrm{B}} = 40$ kWh. We assume that the charging infrastructure is equipped with a 3-phase $400\ \mathrm{V}/16$ A semi-fast charger with a maximum charging power of 11 kW having a charging efficiency of $\eta_{j,\mathrm{c}} = 0.9$.

3.5 Simulation scenarios

The simulations were performed for a range of EV penetrations (0% - 100%, in steps of 10%). We defined EV penetration as the percentage of households that own an EV. The benchmark case with no EVs is included in the analysis for the purpose of reference, which is referred to as the 0% penetration case. We also simulated the uncontrolled EV charging scenario (Unc), where the EVs start charging as soon as they arrive at the point of charging, at a maximum charging rate until fully charged. The results for the proposed MILP-based scenarios are compared with our previously proposed setting with a variable charge rate scenario (hereafter referred to as VC). Different formulations of the proposed MILP solution to the OPT approach were considered to achieve comparable optimality to the VC scenario. The outcomes of the straight transformation of the OPT approach into MILP are denoted as SC. As discussed in Section 2, the MILP formulation of OPT with randomized charging events without group formulation is represented by the scenario SC_1. The MILP formulation with randomization and grouping from two to six groups is represented by the scenarios SC_2-SC_6.

4 Results

This section provides a comparative analysis of the performance of the MILP formulations of OPT for EV charging management presented in Section 3.5 using several performance indicators. The intended objective of the OPT algorithm is to fill the valleys of the non-elastic demand curve utilizing EV demand flexibility by tracking a pre-defined reference signal. Valley filling is primarily employed to reduce the variance in the demand profile. Therefore, we used the variance in total demand as an index to measure the performance of the different formulations proposed which is shown in Figure 2 for the penetration range considered. For the purpose of comparison, the variance normalized to the variance of the 0% penetration is used.

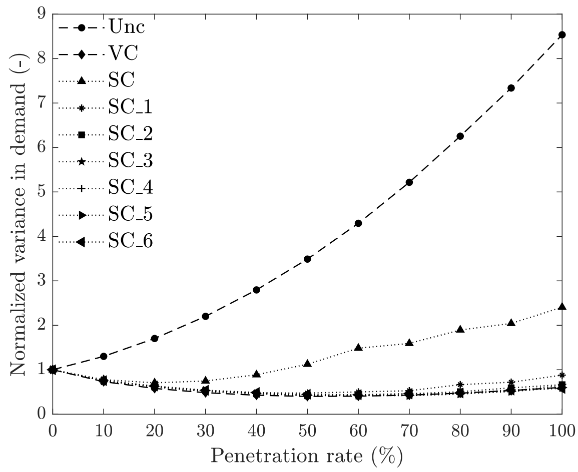

Fig. 2 Variance in the total demand normalized to the variance of the 0% penetration for uncontrolled, OPT with variable charge rate (VC), OPT with semi-continuous charge rate (SC), OPT with semi-continuous charge rate and randomization in charging (SC_1), OPT with semi-continuous charge rate and randomized charging with two to six groups (SC_2-SC_6).

The formulation of OPT with semi-continuous (SC) charging alone reduces the variance in comparison to uncontrolled EV charging, but shows a significant deviation from OPT with VC, which is more noticeable at high penetrations as observed in Figure 2. This can be attributed to the concurrent charging of a high number of EVs at the minimum permissible charging rate during the deep valley periods. The randomization process improves performance to a high extent across all penetrations, whilst still exhibiting a slight variation at high penetration. The inclusion of grouping leads to a performance much closer to the implementation of OPT with VC. Increasing the number of groups results in better performance, however, a group number of four is adequate to achieve similar performance to OPT with VC up to a penetration of 50%.

The valley-filling nature of OPT also aids in reducing the peak-to-average power ratio (PAPR) of the networks. A comparison of the PAPR is shown in Figure 3.

Similar to the results presented in Figure 2, the PAPR of the OPT algorithm with SC charging is on an equitable level to that of OPT with VC only at low penetrations, in our specific configuration up to a penetration of 30%. The SC charging with randomization shows comparable results up to a penetration of 70%. The adoption of grouping further improves the PAPR results. The results also demonstrate that at high penetrations, a high number of groups leads to more favorable results in PAPR.

The OPT method has several other advantages besides valley filling and peak reduction capabilities. We have demonstrated in [12] that the OPT approach positively influences the voltage violations in the nodes and current violations of the cables in the LV grids. Therefore, we evaluated the variations between the different OPT formulations on these two parameters. A

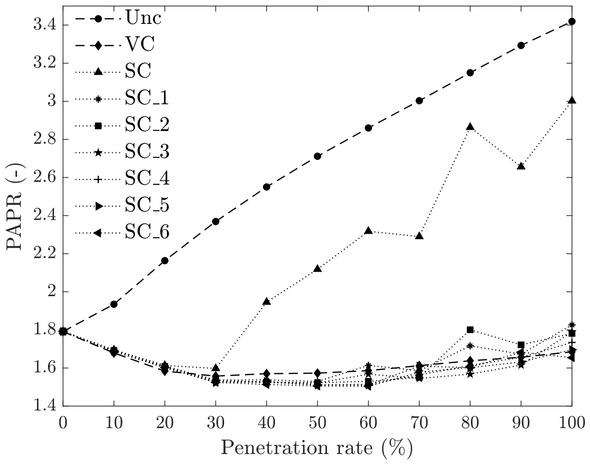

Fig. 3 Peak to average power ratio (PAPR) for uncontrolled (Unc), OPT with variable charge rate (VC), OPT with semi-continuous charge rate (SC), OPT with semi-continuous charge rate and randomized charging (SC_1), OPT with semi-continuous charge rate and randomized charging with two to six groups (SC_2-SC_6).

comparison of voltage deviations for the penetration ranges considered is presented in Figure 4. In summary, the influence of the different MILP formulations on the voltage deviations follows a similar trend to that of the variance and PAPR indices.

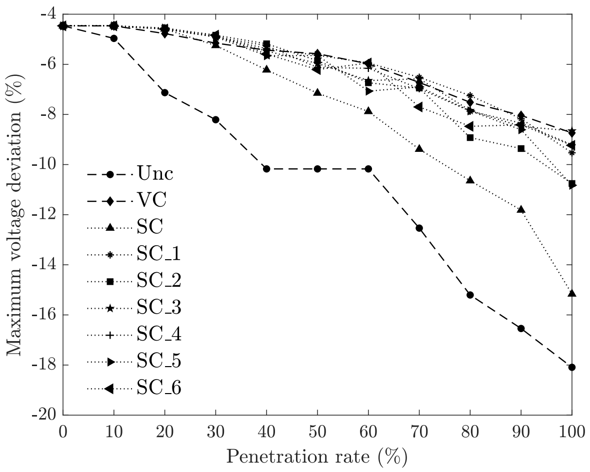

Fig. 4 Maximum voltage deviations in the grid nodes for uncontrolled (Unc), OPT with variable charge rate (VC), OPT with semi-continuous charge rate (SC), OPT with semi-continuous charge rate and randomized charging (SC_1), OPT with semi-continuous charge rate and randomized charging with two to six groups (SC_2-SC_6).

Further, we examined compliance with the voltage standard criteria defined in EN 50160. The selected LV network exhibited a resilient behaviour in terms of voltage. The compliance with EN 50160 was found to be violated at a penetration of 70% at uncontrolled charging of EVs. All OPT formulations with randomized charging provided successful mitigation to these voltage violations.

An overview of the number of events where the cables exceed the permissible currents in the simulated week is shown in Table 1. The number of cables exceeding the limit is denoted in the brackets.

Table 1 Summary of cable overloading events (number of cables affected) within the simulated week

Penetration (%)	Unc	VC	SC	SC_1	SC_2	SC_3	SC_4	SC_5	SC_6
10	2 (2)								
20	40 (2)								
30	111 (6)								
40	203 (8)	4 (2)	6 (4)	4 (2)	4 (2)	4 (2)	4 (2)	4 (2)	4 (2)
50	273 (11)	12 (4)	26 (5)	20 (4)	18 (4)	14 (4)	14 (4)	14 (4)	12 (4)
60	381 (11)	28 (4)	79 (6)	44 (4)	40 (4)	42 (4)	42 (4)	38 (4)	32 (4)
70	527 (12)	66 (4)	256 (10)	102 (4)	102 (4)	96 (4)	88 (4)	86 (4)	72 (4)
80	688 (16)	120 (4)	402 (13)	157 (5)	152 (4)	160 (4)	138 (4)	134 (4)	132 (4)
90	833 (20)	167 (7)	568 (16)	221 (7)	212 (7)	200 (7)	206 (7)	191 (7)	188 (7)
100	981 (25)	203 (7)	632 (18)	261 (9)	260 (8)	259 (7)	255 (7)	234 (7)	235 (7)

In the selected grid, cable overloading problems start to occur already at low EV penetration rates, i.e., at 10%. The OPT with VC mitigates the cable overloading problems up to a penetration of 30% while reducing the overloading problems at penetrations beyond that. The SC formulations with grouping realize comparable results to that of the VC formulation. The SC formulation having random load scheduling and a grouping of six shows the closest performance to the OPT implementation with VC rate in reducing the overloading events.

In summary, the findings demonstrate that the MILP formulation to the OPT algorithm to achieve semi-continuous charging characteristics as defined by the IEC standards, does not perform as well as OPT formulation with the variable charge rate. The introduction of randomization and grouping improves performance, whereby an increasing number of groupings contributes positively.

5 Conclusion

We present a decentralized charging scheduling algorithm that is practically feasible, requires less communication and computational cost, and complies with IEC 61851 charging standard. The primary objective of the algorithm is valley filling, achieved by optimally tracking a target power signal exploiting the flexibility of EVs. The method exhibited promising results when used in a previous implementation with a variable charging rate which is not in compliance with the IEC standards.

In this study, the proposed method is extended to ensure compliance with the IEC standards. A mixed-integer linear optimization formulation was adopted to realize the semi-continuous charging characteristic to meet compliance with the IEC standards. The results show that the MILP formulation fails to perform successfully compared to the variable charging rate implementation, indicating a 2.8 and 3.9-fold deviation in the variance in demand at 50% and 100% penetration rates.

To overcome this limitation, the method is extended with a modification involving a randomization and grouping mechanism. The randomization process alone improves the performance of the variance in demand, being 1.2 and 1.5-fold with respect to the variable charge rate at 50% and 100% penetration rates, respectively. The adoption of the grouping enhances the performance further, in particular for high penetrations. The best performance was achieved with six groups; the highest number of groups we employed, with a variance in demand of 1.04 times that of the variable charge rate, at 100% penetration rate, indicating the proposed method to be a feasible implementation.

The performance of the proposed method subjected to the various uncertainties associated will be considered in a future implementation. The incentives for consumer participation and the policy framework for the implementation in practice remain to be developed by the DSO.

6 Acknowledgements

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Publication E

Author Contribution

- Literature analysis of publications in the field of DSM of EVs under uncertainty and different forecasting method for demand predictions
- Implementation of the neural network-based demand prediction model
- Concept of the MPC based simulation framework
- Implementation of the simulation software in MATLAB and evaluation
- Analysis of the results
- Manuscript preparation