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Industrial Electrical Engineering and Automation

Congestion Management of EV Charging in Distribution Networks

A Framework and Evaluation of the ANM4L Control Algorithm

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A Framework and Evaluation of the ANM4L Control Algorithm

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Preface

This thesis was carried out in the spring semester of 2022 at Temple University, through the Faculty of Engineering (LTH), Division of Industrial Electrical Engineering and Automation (LTH) at Lund University.

I would like to express my appreciation and gratefulness to my supervisors Olof Samuelsson and Martin Lundberg a LTH, and Liang Du at Temple University. It has been a challenging task to conduct this thesis remotely and independently, where both Olof and Martin have shown great encouragement and support in practical and theoretical issues. Martin has been commendable in his guidance and has shown great interest in providing input with the simulation model and the results, while Professor Du acted as support on ground when things felt heavy and distant.

I would like to dedicate this work to my parents Maria and Andrzej, who always been supportive all throughout my university studies. Their unconditional love and support for me is something I am truly grateful for.

Adam Rosandell

Adam Rosandell
Lund, September 18, 2022

Abstract

The societal integration of electric vehicles (EVs) imposes several challenges on the electrical grid, where congestion and overcurrents through related components are of focus for this thesis. Active network management through control systems is one flexible solution to this problem, and in the project Active Network Management for All (ANM4L), a congestion management algorithm utilizing PI controllers has been developed. It has the possibility to control the active power (P) of the network by curtailing the charging power for the active EVs when overcurrents are detected. The focus of this paper is to evaluate the effectiveness of the ANM algorithms performance in achieving congestion management, by comparing with an uncontrolled scheduling and a decentralized tariff-based scheduling. The purpose of the latter is to investigate the potential for congestion management without aggregator involvement and to minimize the charging costs for the EV owners by scheduling all charging to low-cost hours. The test network was designed without consideration of extensive EV charging, illustrating a present day network which might have been dimensioned decades ago. The maximum number of actively allowed EV units in the network was led by the ANM controlled scheduling at 53%, followed by the uncontrolled (37%) and tariff-based (24%) scheduling. This illustrates the future network and societal constraint in terms of EV integration. For the ANM implementation, two prioritization schemes were implemented. In a 10-bus low voltage test network with 11 kW home-charging stations, the ANM algorithm proved to be efficient in alleviating the network constraints whilst maintaining the EV owners energy demands when owners with the highest instantaneous power consumption experienced the highest curtailment. The tariff-based scheduling on its own proved to severely stressful on the network due to simultaneous tariff activation, but was in combination with the ANM algorithm able to alleviate network congestion. Total charging costs were reduced by 36 percent, although 10 percent of EVs were not able to fulfill their charging requirements, indicating difficulties in societal adaptation in contrast to monetary lucrativeness in future implementations.

List of abbreviations

Power System Related

- **PV** - Photovoltaics
- **RES** - Renewable Energy Source
- **DER** - Distributed Energy Resource
- **DSO** - Distribution System Operator
- **TSO** - Transmission System Operator
- **LV** - Low Voltage (Residential outlets, 230 V)
- **MV** - Medium Voltage (Distribution network, 20-40 kV)
- **HV** - High Voltage (Transmission network, 130-400 kV)

Electric Vehicle Related

- **ICE** - Internal Combustion Engine
- **BEV** - Battery Electric Vehicle
- **FEV** - Full Electric Vehicle
- **HEV** - Hybrid Electric Vehicle
- **PHEV** - Plug-in Hybrid Electric Vehicle
- **SoC** - State of Charge
- **TCP** - Transmission Control Protocol
- **V2G** - Vehicle-to-Grid

Contents

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1 Introduction

Society is undergoing a massive paradigm shift to combat the challenges presented by global warming, which is linked to the anthropogenic emissions of carbon dioxide (CO_2) and other greenhouse gases. The automotive industry is seeing a disruptive change in demand for non-fossil based driven vehicles such as EVs in an attempt to decarbonize and reduce the carbon emissions linked to the transportation sector which accounts for 21 percent of global emissions, 75 percent of which are linked to road vehicles [1]. EVs are continuously increasing its market penetration as the world transitions to a more sustainable means of transportation, and Sweden is at the forefront of not only EV research and development but also in societal adaptation as governmental incentives are being introduced and facilitate for consumers to transition from conventional ICE vehicles. EV sales, including HEV, PHEV and FEV, have risen by 82 percent annually since 2019 and accounts for 45 percent of the Swedish noncommercial light-duty vehicle fleet (2021) [2]. Still, the road to global acclimation requires further introductions of policy support as it is the key driver for adaptation according to the Global EV Outlook 2021 report [3]. The key policy drivers are fiscal incentives, gradual tightening of the conventional and present fuel economy, and strategic deployment and accessibility of charging infrastructure.

Projected energy demand due to increased presence of electric cars and general electrification of society is expected to grow with 25 percent in the coming decade, and the issue of capacity challenges emerges in LV distribution networks due to the erratic high power consumption associated with EV charging [4]. Uncoordinated charging on a larger scale may negatively impact the grid in several ways. Large concentrations of simultaneous EV charging may cause surges in power demand and result in voltage drops and line losses, thus affecting the power quality. According to the EN50160 standard, LV grids are allowed to have a ± 10 percent voltage deviation to maintain stability [5]. Research based on a 34-node IEEE test feeder shows that the voltage deviation reaches 10 percent for a 30 percent EV penetration rate case [6]. As the power grid transitions to a more decentralized structure with intermittent RESs such as local PV production, DSOs are consequently required to impose enhanced control mechanisms and apply active asset coordination to maintain grid stability and ensure supply security to their connected customers. Traditional network reinforcements may be deemed excessive due to their immense investment needs and may economically and temporally not correspond favorably to the congestion issue presented by EV charging [7]. Congestion occurs when related equipment such as transformers, overhead lines and cables exceed their transfer capacity.

An illustration of this is shown in Fig. 1, where it is clear that EV charging lacking coordination may invoke transformer overloading which is set at 150 percent of its rated value [1]. An excessive amount of uncoordinated charging increases the peak load demand and reduces the reserve margins available, and may introduce reliability issues [10]. Although these assets are designed to withstand temporary overloads, dangers such as premature equipment deterioration due to prolonged overcurrents and thermal overload decreases their life span as their per-cent ageing increases linearly with EV penetration levels [11].

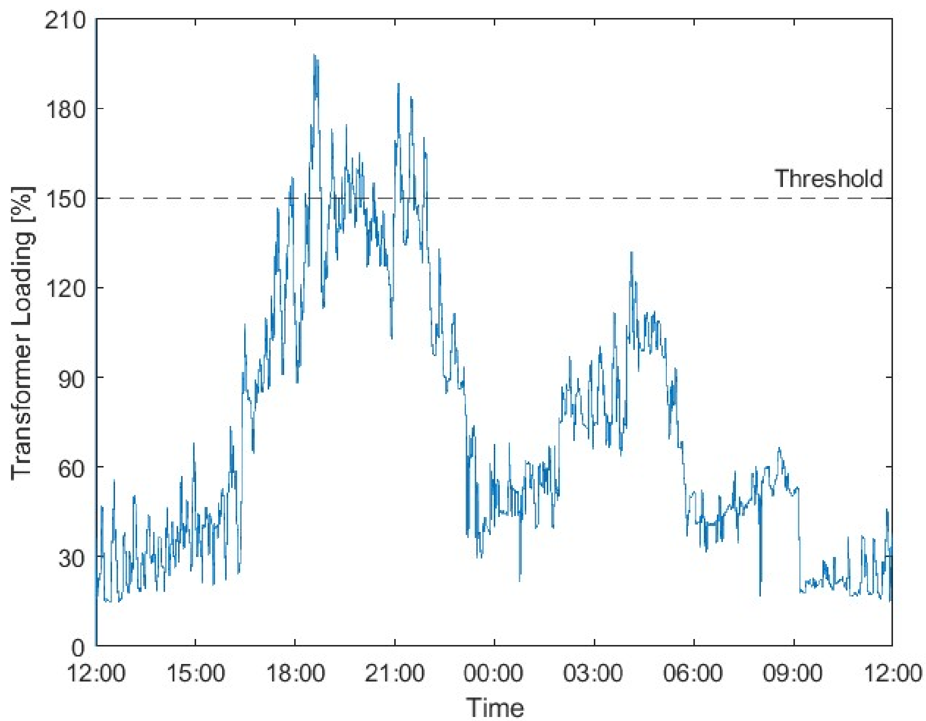

Figure 1: Transformer loading without EV charging coordination.

The consequences of this may impose outage risks which ultimately results in premature and undesirable costs for all operators and patrons active in the network.

[1]Transformer overloadings are generally set by temperature benchmarks, but since these inertial instantaneous power values are monitored [8] [9]

In determining the power outage hazard probability associated with simultaneous EV charging and increasing EV penetration levels, researchers at the University of Twente could significantly reduce the outage risk by slightly reducing the LV feeder loading limits whilst maintaining the energy demand requirements through alterations of the charging duration [12]. By modelling a coupled transportation and power distribution system, researchers at Hanoi University were able to reduce the total procurement cost for congestion management by 24 percent by integrating demand response (DR) measures for regular power demands in comparison with traditional EV charge flow methods [13]. Since FEVs rely solely on electric propulsion they are entirely dependant on their on-board energy. When charging currents are limited users may need to seek to alternative charging stations which negatively impacts the adaptation rate for non-fossil based vehicles, which conclusively hinders the transition to a more sustainable vehicle fleet.

The advanced deregulation of the electricity market has led to a revolution in the sphere of grid management. Currently, small-scale production by prosumers who interact in the market by selling excess energy does not pose problems due to their present marginality. However, these systems do bring producers and consumers geographically closer to each other, which reduces the losses associated to the transmission and distribution of electricity. This is significant as line losses account for 5 percent of produced energy and 30 percent of transmission and distribution costs [14][15]. Additionally, the fiscal incentives constructed by governments develop production system based on RES, and regional aids and tax exemptions further expedites the upheaval of small-scale producers to be connected to the distribution network. At this rate, a point in time might occur where this poses critical hazard, where voltage profiles get further affected. The non-uniform distribution of their connections and the intermittent nature of their energy production will also affect the forecasting estimates which further complicates the future grid operations.

This thesis is in part in collaboration with the Active Network Management For All (ANM4L) project initiated by the Research Institute of Sweden (RISE). The aim for ANM4L is to cover the exploitation of flexible network assets such as converter-interfaced generation, loads, battery energy storage systems (BESS) and EV charging, as well as improve grid utilization and defer grid reinforcements whilst maintaining safe operating conditions [16].

An evaluation of their voltage management algorithm was conducted, where the controls managed the active (P) and reactive (Q) power injections with the voltage level as input. It proved to be successful in adjusting the voltage level by consuming reactive power, and when needed curtail the active power and thus increase the available grid capacity in a distribution level network model [17]. As a continuation, the next step is to evaluate their congestion management algorithm in a similar fashion.

The transition to a more sustainable transportation sector requires a scrupulous planning of the infrastructural foundation and should take in consideration the limitations found in LV distribution grids, whilst ensuring for safe operations and limiting the potential damage through LV grid components. Management of EV charging constitutes an imperative step in maintaining this stability. As the number of EVs increase in society they impose a congestion risk in the distribution grid when not enough power can be made available. In future deployments it is imperative to have pre-evaluated the different challenges and opportunities found with utilizing different charging strategies, for which this thesis will study *uncontrolled*, *controlled* and *tariff-based* charge scheduling. Therefore, it is of interest to investigate how a safe and reliable grid operation is ensured whilst allowing for increased car charging in society and evaluate the economic results of introducing incentives and disincentives during hours of overload.

1.1 Problem Statement

The objective of this thesis is to establish a framework and evaluate the functionality of the ANM congestion management algorithm, and gauge an understanding of its practicality and challenges emerging. The goal is to prevent grid overloads and premature component degradation by dispatching the requested demand whilst satisfying EV owners needs, either by aggregator authorized load control and load shifting, or through the introduction and employment of price-based incentives. Specifically in the formerly mentioned measure, currents shall be limited through congested components such as transformers, overhead lines and charging substations by controlling the active power flow upstream. In the latter, charging should be conducted during low-peak hours to facilitate for cost-benefiting the EV owners and DSOs.

From an initial standpoint there are ultimately two questions that need to be addressed and answered, namely:

- How well does the ANM congestion management algorithm manage the congestion bottlenecks and prioritize the load control and load shifting throughout the affected components?
- How do the presented charging modes affect the grid load, and which economic and infrastructural challenges and opportunities do they bring?

1.2 Delimitations

To ensure that the scope of this study is accurately defined and bounded, delimitations must be set. The primary focus of this study is the impact and control of the distribution side of the grid, for which generation will not be taken in consideration. The ANM algorithm will only be evaluated for a fictive low-voltage level (0.4 kV) network model with BEVs represented by their batteries as the exclusive units of consumption, not taking into account any aspects of battery degradation or overall vehicle performance that may occur as a consequence. The external MV grid is represented by an equivalent, and reactive losses are neglected. Previous studies of similar nature have also evaluated the factual impacts of the thermal degradation of the affected components, but for the sake of this thesis this has been omitted. Possible faults as a result of congestion has also been omitted, and whilst energy demands have been taken in consideration, daily mileage fluctuations or projections have been bypassed. Since three-phase 11 kW Level 2 charging is of observation, voltage unbalances due to imbalanced single-phase charging has been neglected.

1.3 Related Works of Others

Several studies have been conducted investigating congestion management with different control strategies, mostly focused on residential energy cost minimization and thus including market price parameters and bidding strategies. Authors of [18] propose a dynamic power tariff (DPT) method for congestion management of EVs with high penetration levels, which proves to be successful without the need of price sensitive coefficients. With this implementation, the authors expect higher commitment from the aggregators to participate explicitly in the market, implying more certainty for network alleviation. Authors of [19] confirm this in a PV and V2G implementation, where negative feed-in power flows are existent and may invoke negative regulation prices.

In 2021, Göteborg Energi introduced a new pricing model for its customers which seeks to reduce power peaks by including a power tariff in the network tariff for households [20].

With the emergence of further local generation and spatially stochastic charging demand, authors of [21] investigated an optimization of flexible charge scheduling through microgrid operators (MGOs). With the introduction of new participants in decentralized markets such as distributed generation aggregators (DGAG) and electric vehicle aggregators (EVAG), competitive market actions may counteract each other. By introducing a framework for combined operations they hope to optimally take advantage of competitions in terms of day-ahead congestion management.

Another conflict that may occur is in the topic of curtailment fairness, since the radial structure of grids means that voltage sensitivity for P variations increase in distance to the feeder transformer, thus requiring households furthest from the feeder to experience the largest curtailment. This issue can be neglected in smaller networks, for instance residential areas, where distances to the feeder are generally shorter. Control systems for active load power in residential real estates have been simulated in [22], where household currents were controlled to allow for EV charging to be conducted. Available EV charging current capacities were calculated as the difference between maximum allowed peak currents and the measured real time currents and were kept in a tolerance band, which proved to be successful in eliminating peak currents and enabling for greater comfort levels for EV owners. Valley filling was obtained during off-peak hours as a result, and while enabling for higher average charging powers, cheaper night-time electricity could be better utilized thus allowing for DSOs to bring down their operational costs. The ANM algorithm for congestion management is a centralized system which seeks to obtain congestion management in a similar fashion, based off of a flexibility dispatch prioritization [16]. This allows for the operator to choose from multiple control actions through manipulation of the dispatch list, in comparison to a predetermined uncoordinated decentralized system. Curtailment and power transfer loss, operational and utilization costs as well as environmental impacts can hopefully be minimized when prioritization can be flexibly based off of asset characteristics, network topology related location and specific grid constraints.

2 Theoretical background

2.1 The Power System and EV Charging

Traditionally the power flow has exclusively been from the HV production sites to the LV consumers, but with the emergence of small-scale DER aggregators, operations of the power system has become increasingly decentralized. Rather than the grid being a passive and radial unidirectional power conduit, there is an increased support in bidirectional information exchange and energy flow to and from consumers as the current grid is not well prepared to host high proportions of dispersed power production. Based on the type and level of charging, which will be discussed in Section 2.2, EV charging is conducted at the bottom layer of the grid in regional and local networks operating under their respective distribution network(s). Residential charging which accounts for 80 percent of all EV charging is conducted at a 230 (LN) or 400 V (LL) level depending on the phase utilization [23]. Residential buildings are connected to the local network through secondary substations which include step-down transformers which brings the voltage down from 20-40 kV which is considered medium voltage (MV) levels. The local networks are relayed from the regional networks which operate at high voltage (HV) of 130 kV through substations. The top layer is considered the transmission network which operates at extra high voltage (EHV) levels (400 kV) and transports electricity from the generating facilities through alternating current (AC) before reaching the distribution networks.

Transmission of power is done through alternating current (AC) as transformers easily permit for high voltages which reduces resistive losses. This transmission brings some notable phenomenons which presents challenges which must be addressed. The sinusoidal characteristics of alternating currents gives rise to different components which depend on the phase shift between the voltage and the current, resulting in the categorization of powers. These are addressed as apparent, active and reactive powers. Active power is what the EV factually can utilize for its charging, but reactive power is still formed in the power cables and is used to energize the magnetic cores of the transformers in the distribution network. The apparent power is a vector combination of the above mentioned and is the literal power consumed in the network, but since reactive power losses are generally low in distribution networks due to the shorter distance these are generally of low concern.

The imminent concept of Smart Grids presents a innovative structure for the electricity industry with new features and possibilities in terms of grid control, management and general operation. One example is the communication infrastructure such as smart metering and demand management systems, which can provide real-time system variable information such as voltage and current levels, active and reactive powers and line losses. These individuals components are important in classifying individual appliances from smart meters for future load disaggregation purposes, which will be briefly discussed in Section 3.2.2, but moving forward this implementation will be assumed.

2.1.1 The Distribution Network

The three distinctive layers and two networks which the Swedish electrical grid is composed of operate with different operating parameters and responsibilities. The distribution networks responsibility is to deliver energy to all its connected customers, and is increasingly required to connect different units of distributed generation (DG). It is further divided into two specific functions: energy delivery and supply. The former is kept under monopoly ruling under the jurisdiction of a local distributor which acts as a network operator, and the latter is market driven under competitive circumstances. LV grids are traditionally composed of radial feeders, i.e only containing one path between two nodes, and cables with low X/R (<1) ratios due to having shorter distances in between nodes. The system liability for the distribution networks lay in the hands of their respective proprietors, i.e the companies who own and operate the regional and local networks. Their comprehensive responsibilities are to ensure that their respective distribution network are secure and both environmentally and economically sustainable [24]. The modernization of present day distribution networks are followed by an increased utilization of EVs and accompanied demand respond (DR) services in residencies. In the future, real-time congestion management will be conducted through flexible charging scheduling and load curtailments [25]. In context to the US power grid which follows a more deregulated electricity market, units of DG are generally not connected to their overlying system operators (SO). Henceforth, encouragement for demand-adjusted charging is fundamental for maintaining future grid stability [26]. Assessments of the regional impact of EV charging in distribution networks has been extensively research, but further investigations are looking into the interaction between distribution and transmission network systems as well. System-wide impacts may assess aspects such as CO_2-emissions reductions and additional costs due to EV integration, and estimations of primary energy consumption reductions.

2.2 EV Development and Grid Integration

Advancement made in the Smart Grid and battery industries has contributed to this development as increased battery capacities permits for greater mileage and technological development has driven down the costs, and improved the charging infrastructure by enabling for higher charging powers and greater charging accessibility [27]. There are notably three different levels of charging scenarios possible in present day. Level 1 charging refers to the first generation household outlet charging which is limited to 3.7 kW, but due to its low power the adaptability is the lowest of all levels. Level 2 EV charging also refers to household charging but through the employment of wallboxes that permit for higher charging powers and can be utilized at the EV owners own premises, between 3.7 kW and 11 kW. Level 3 EV charging refers to DC supercharging through specialized charging stations typically deployed at highly concentrated car areas such as shopping malls, parking lots and gas stations, between 11 kW up to 150 kW. The IEA forecasts that Level 2 charging will initially be of concern for LV distribution networks, more specifically residential areas, and future concerns may be linked to wholesale market prices due to an unbalance in energy demand [3].

Current retailed versions of FEVs operate solely on electric energy propulsion and have battery capacities ranging from 20 to 100 kWh and mileages ranging from 100 to 530 km. Manufacturers are experimenting with different battery technologies, but the most commonly used is the lithium-ion battery (Li-Ion) which is expected to remain dominant in the coming decade due to its high cyclability and affordability [28]. Commercial wallbox models such as the *InCharge* allows for 3.7 kW of charging on a 16 A single-phase, which is regulated by Swedish legislation [29]. By utilizing the three-phase connection (230/400 V) found in residential buildings one can obtain 11 kW of charging which allows a consumer to fully charge a Tesla Model 3 with 50 kWh battery capacity in less than 5h. International EV conductive charging standards are defined by IEC 61851. Standard IEC 61851-1 states that the maximum AC charging current can lay in the interval 6-32 A per phase for Level 2 charging, but reports have stated that EVs cannot utilize charging currents less than 8 A [30]. Grid integration's are not solely limited to plug-in charging, but research is also conducted regarding conductive charging such as the project Elonroad in Lund. Their solution consists of a conductive rail which lays on top of the road, with short grounded segments arranged along the track. A steady rectified current is supplying the on-board battery whilst driving over the track, and by developing this solution the team hopes to contribute to the flattening of EV charging demand throughout the day by introducing an effortless charging solution [31].

2.3 Charging Strategies and Consumption Patterns

Residential consumption patterns are ought to become increasingly altered with the increased presence of EVs. This is due to the fact that EV charging significantly intensifies the power demand from the grid and disproportionately increases the power peaks in contrast to the operations and consumption of a typical residential consumer. The consumption of each household varies significantly based on factors such as geographical location and climate, as well as marital status and number of occupants, but is quite predictable as an aggregate and solely does not present any issues on a distribution network level due to its modest demand [27]. EV charging on the other hand is more stochastic due to the temporal and spatial usage patterns as it can be conducted at different levels, as discussed in Section 2.2, and the daily energy demand may differ substantially from day to day. Fig. 2 depicts the daily aggregated concentrations of household and EV charging loads for a given residential household, suggesting that the biggest concentration occurs in the early morning hours (03:00-07:00) before commuting followed by charging occurring in the afternoon (18:00-22:00) due to commuters returning home. Although the predominant charging is conducted in the early AM hours prior to commuting, EV charging occurring in the PM hours coincides with peak base load hours and exacerbates the total power demand. Factors such as load demand, charging power, charging patterns and plug-in time are all key factors affecting the distribution transformers. The most significant impact seems to be the market penetration level which is expanding rapidly, for which it is of importance to investigate its current and future effects on the electrical grid [3].

Strategies such as EV integration with PVs and V2G are promising in alleviating the excess load demand presented by EVs. This is especially true during the daytime, as these functionalities can be utilized to flatten out the peak demand and aid in frequency regulation. Deterministic and stochastic dynamic programming PHEV coordination techniques were discussed in [32], and PHEVs can be utilized to provide ancillary services which enable grids to self-regulate during emergency and congestion conditions and thereby improving grid reliability and system efficiency, as well as the delivery security. While the technical feasibility's of these concepts have been extensively demonstrated, a crucial barrier for their practical implementations is economic concern. According to [33], a realistic assessment of the economics of V2G implementations requires a modelling of an homo economicus agent which exploits all relevant data for economic maximization of utilities. Since this is not prudent, smart control strategies assembled with real-time data, prediction algorithms and practical battery models is suggested to improve the strategy for agent market participation.

Going forward, this concept will not be considered in this work.

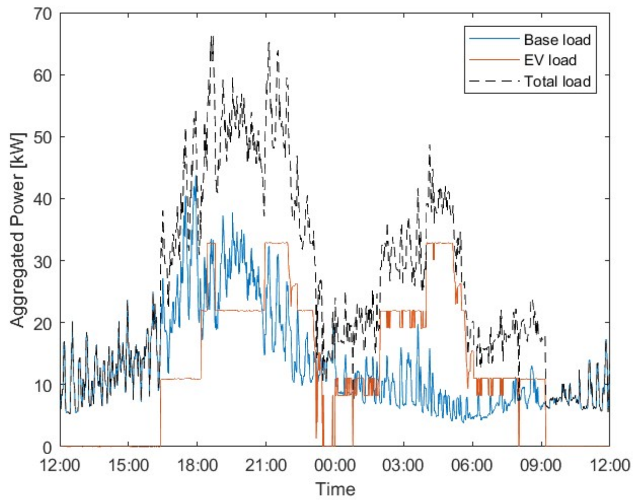

Figure 2: Aggregated base, EV and total load.

Different charging strategies has been heavily discussed in literature as different solutions bring distinctive challenges and opportunities. The most intuitive and adopted charging strategy is generally referred to as dumb charging or uncontrolled charging, which as the name suggest, does not require any particular intelligence to perform. This is when a user simply connects their vehicle to their charger at the most convenient time instance and starts the charging cycle until it reaches its desired SoC, with the main benefit of this method being its simplicity. The second strategy, smart charging, is one that generally introduces optimization and EV aggregators. EV aggregators are entities located at an intermediate level between the DSOs and EVs, specifically located at the LV transformer (See Section 3.2.1). The benefit of implementing intelligent measures is that through communication links and computational power, users may experience cost reductions and greater convenience, and utilities may be able to distribute power for grid balancing and stress reduction. On the other hand, grid synchronization and profitability concerns are the main challenges at this current moment of time. For this implementation to be proactive, a real-time communication link, such as Transmission Control Protocol (TCP) is necessary [27] [2]. This spatial distribution hinders DSOs to adequately address the rising concern of network congestion with traditional methods as described in the following section.

[2]Reference documents on this topic are the standards IEC 61851 and 62196, and ISO 15118.

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3 Congestion Management

Grid congestion occurs when transmission or distribution lines are unable to accommodate for the desired demand during peak hours, and can be presented either by unprecedented demand spikes or by capacity constraints as is the case during grid maintenance. Congestion impacts the reliability of the grid and affects its performance and efficiency, and during overload conditions, line losses become of concern as they approach their thermal limits [34] For consumers, congestion may result in elevated utility prices as electricity retailers lose their accessibility to cheaper means of generation sources [35]. The societal impacts of grid congestions cannot be underestimated. In 2002, prior to the second most widespread power outage in US history, the regional TSO PJM[3] Interconnection quantified the costs related to congestion under their administration. Solely in their operating area, which coordinates most of the Northeast of the US, the costs associated were in the billions of dollars annually [35]. The following outage affected 55 million people in up to 4 days. These costs were primarily generated as the difference between the available market capacity and the cost paid for the (more expensive but) deliverable energy. Although the following blackout was not a direct consequence of the congestion issue, according to the North American Electric Reliability Corporations (NERC) final report, one of the main causes for the blackout were a lack of operating telemetry data and effective communication links [35].

Traditionally, congestion management has been dealt by grid reinforcement by TSOs and DSOs. Utilities and suppliers worldwide spend billions of dollars annually to expand their transmission capacities to accommodate for future generation and growing demand, which reduces the line losses associated with thermal overloads [36]. Installed distribution transformers were designed without the consideration of substantial charging demand and with long operating life spans, up to 40 years [7]. Since production is projected to become increasingly intermittent and consumption further spatially and temporally variable, these traditional solution are deemed economically and reliably inappropriate. One of the more feasible solutions in terms of peak demand reduction is to utilize PV production to coincide with EV charging to reduce the power requirements from the grid. This centralized option is becoming increasingly attainable as PV and EV penetration rates correlate and their combined adaptation expands. Authors of [37] studied the aggregated impact of rising EV and PV penetration levels in distribution networks, and found that EVs are able to help decrease the excessive PV energy without any charging coordination strategies.

[3] Pennsylvania-Jersey-Maryland Market, including 14 US states.

They also state that improved power electronics and adaptation of smart meters are imperative. One solution is to optimize the power flow through economic dispatch [36]. The need for flexible adaptation has given rise to the development of new management strategies which allow for greater resilience. Direct approaches involve curtailment of load and local generation, whilst indirect approaches may motivate prosumers by different incentive-based demand response mechanisms [26]. Although they may have an impact on the demand flexibility, more often than not they bypass the physical constrains that are present in the grid.

3.1 Demand Response

Demand Response (DR) is a fundamental mechanism in a smart grid environment as it combines and tunes both the production and consumption of time-varying instances. This can be done through transmittance of different pricing signals to the load controllers, and can contain information about the RESs production, electricity costs or available grid capacity [27]. As an optimisation and loss reduction measure, consumers can reduce their utility bills and receive incentives during peak hours, while utilities can reduce their import dependence and evade capacity shortages. Implementation of DR programs can be coordinated in several architectural structures, either as centralized, decentralized or with a hierarchical structure. The categories refer to the level of authority on which the charging arrangements are determined given the specific constraints and objectives. The centralized (i.e. DSOs) approach has several advantages in terms to charging control reliability and is easily integrated into pre-existing power system controls. The drawback is the high necessity of data in order to execute accurate scheduling by the central controller, as well as that the optimisation complexity increases exponentially with increasing participating units. Hierarchical controls are advantageous in terms of cost minimization and overall system operations when large scale EV coordination is of focus, since EV types and local operational constraints in power systems are efficiently maintained this way. Lastly, decentralized systems isolate the system complexities to the concerned area allowing for easier maintenance and supervision, enabling for easier implementation for smaller networks such as residential areas where feeder distances are shorter and control can be sovereign. The majority of coordinated charging schedules are either centralized or hierarchical and require detailed EV user information to function properly. Fig. 3. provides a schematic representation of these categories.

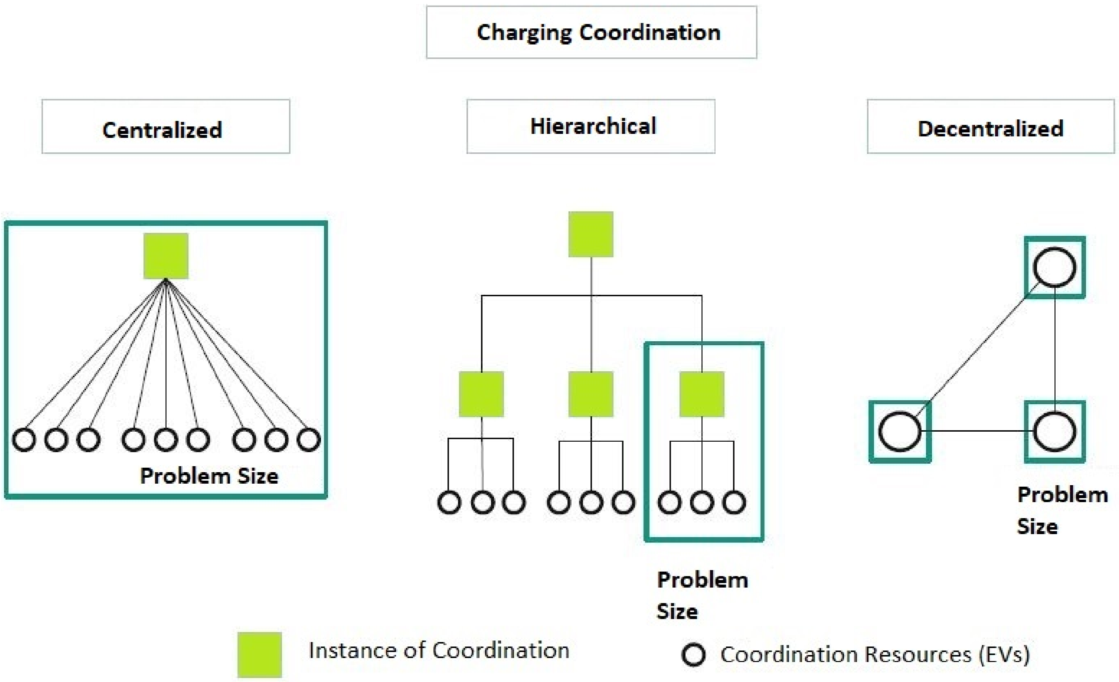

Figure 3: EV charging coordination architectures.

Implementations of DR are usually divided into two (three) categories, namely Direct Load Control (DLC), Load Scheduling (LS) and Tariff Policy.

3.1.1 Load Control

Direct Load Control, also known as load shedding, is used to reduce certain demand by curtailing the consumption based off of a specific threshold. This is often associated with the term peak shaving. In it's simplest form, it can be conducted as followed: Once a power threshold level is surpassed, the load control process initiates. Each individual household in the residential area are arbitrarily classed and ordered in a group and sorted in a load control list. The list follows a first-in/first-out (FIFO) structure and does not require any prior energy notifications or consumption projections. The second option is to implement an optimized version, which includes energy requirements and time constraints. Based on this, the EV aggregator can determine the maximum time period for which they can receive DR commands, τ_{DR}, and an estimation on the total power reduction (DP, Dynamic Power) that it can administer to the network, DP = P_{ON} - P_{OFF}.

The objective for the aggregator is thus to manage $i \in N$ EVs of N users in such a manner that:

$$P_T(t) = \sum_{i=1}^{N} p_i(t) - DP_i(t) < B \tag{1}$$

where P_T is the total power demand through the transformer, p_i is the individual EV owner demand, t is the time of the DR duration τ_{DR} and B is the power threshold of the network as defined in Fig. 4 [27]. To enable for the continued legal, infrastructural and societal adaptation of EVs, it is important to take in consideration the user comfort and component ratings.

3.1.2 Load Scheduling

Load Scheduling (LS) is considered the second-most significant DR implementation and manages non-emergency and delay-tolerant power tasks which are categorized as such which may be interrupted or delayed to other time instances. EV charging is one such task, where the owner generally does not bother when his/her car is charged during the night as long as the required battery charge is obtained in the following morning. The objective of LS is to maintain load balancing and achieve cost minimization for consumers by transferring delay-tolerant tasks to off-peak hours, which generally occurs during the late-night and morning hours (22:00-08:00). By considering a residential area with N EVs, the instantaneous power demand through the LV transformer can be denoted by:

$$P_T(t) = \sum_{i=1}^{N} p_i(t) \tag{2}$$

where p_i is the power demand for charger i. An example of Direct Load Control and Load Scheduling is presented in Fig. 4.

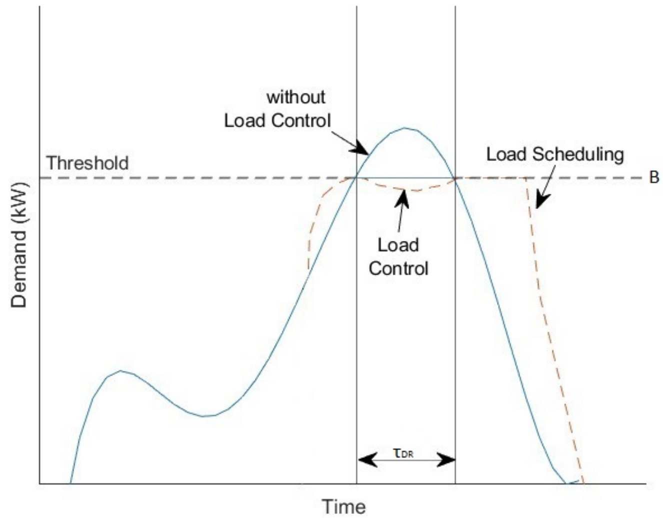

Figure 4: Example of Direct Load Control and Load Scheduling.

3.1.3 Tariff Policy

Residential households in Sweden can either have fixed or variable electricity prices, where the latter has historically been the cheaper alternative in the long run for the vast majority. The electricity market in Sweden, including the Nordic countries, is composed of three markets. Elspot is where electricity is traded on an hourly basis for the day-ahead market. During the day of delivery, Elbas is the market for intraday trading, where bidding aggregators may place bids for up to an hour before delivery. Both of these are governed by Nord Pool, and additionally electricity is also traded through long-term bilateral agreements through Nasdaq OMX Commodities [38]. This Nordic market provides opportunities for demand and generation to compete based on price dependency, but at the current moment only large scale industrial consumers are able to participate directly. The installation of smart meters will allow for small-scale operators to participate more directly. In comparison, end-users can participate in the PJM electricity market's day-ahead energy, reserve and capacity markets through curtailment service providers (CSPs)[4]. One issue is that the retail prices are set by the regional authorities, which are disconnected from the operations of the federal agencies.

[4]The role of CSP is defined by PJM as, "the entity responsible for demand response activity for electricity consumers in the PJM wholesale markets." [39]

The tariff policy based implementation is a price and incentive-based DR, where EV owners are decoupled from the EV aggregators and instead are incentivised to charge during valley hours of low electricity prices. Its success depends not only on the rate structures offered by utilities, but also on the EV owners willingness to adapt and utilize this policy, for which a reasonable assumption is that only a part of the EV load will eventually shift to these off-peak hours. There are even concerns regarding high level of EV penetrations, stating that the grid may reach its technical limits in the event of an considerable load shift to the lucrative valley hours [30]. Although the hourly prices vary periodically based on seasonality and daily based on day-to-day demand and supply, generally the cheapest hours occur during the hours of 22:00-08:00, and peak at 08:00 and between 17:00-22:00 [40]. Although the traded electricity price fluctuates hourly, the utility companies charge a volume weighted monthly average of the spot price to its customer which then pay a monthly bill [41].

Although hourly billing is offered free of charge for Swedish household customers, incentives for greater impact and adaptation need to be further introduced [20]. This allows for greater participation and decentralisation of the electricity markets, which is a key driver for global acclimation and adaptation of EVs. Some challenges concluded in the follow-up report [41], is that few users have shown interest in hourly billing contracts due to the drawn-out installation process, which can take upwards of 30 days to complete. According to the Swedish National Institute of Economic Research (Konjunkturinstitutet), residential customers price sensitivity is far less that of energy-intensive industries, and with a non-elastic price sensitivity, it is not obvious that a transition in billing agreements will cause residential customers to adjust their consumption to the extent necessary to cope with an increased presence of EVs [42].

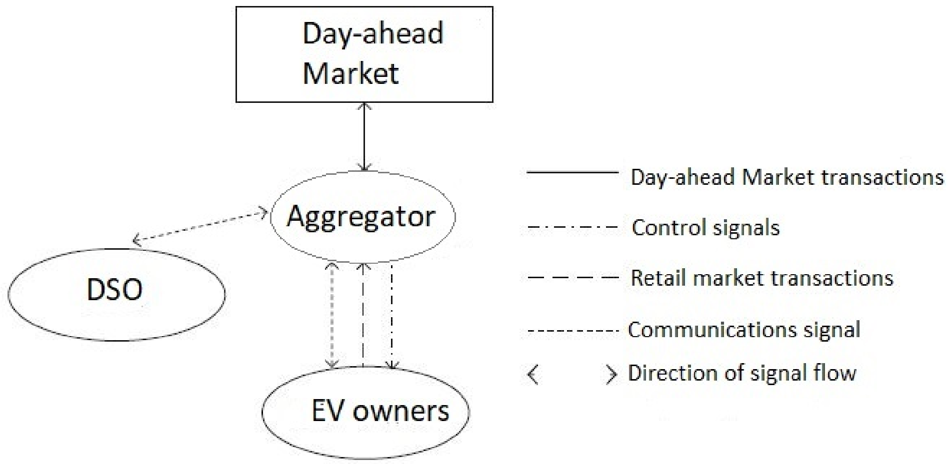

Figure 5: Overview of market entities and their interactions in the physical markets.

3.2 Real-life Implementation

To realize a viable implementation, real life constraints and technologies have to be in harmony. The following section will describe a proposed real-life implementation of a DR measure and it's inherent components.

3.2.1 EV Aggregators and Ancillary Services

A crucial step in the development of Demand Response measures is to allow for EV aggregators to be active participants in the distribution network. EV aggregators are operators in the electricity market who's role is to efficiently manage and utilize the distributed power available to (not solely) the EVs and act as a intermediate between the grid operators and EV owners as per Fig. 5.

Ancillary services are crucial in the transition to a more decentralized market as it permits for smaller market patrons to participate in the electricity markets and support the utility companies in their quest to efficiently manage the electricity networks [43]. Their appearance in the network depends on the the specific solution that is desirable, with the respective coordination architectures being depicted in Fig. 3. Different coordination procedures have been researched in literature with different outcomes, but generally they are based on mathematical optimization problems.

According to [44], which comprehensively studied the integration of PHEV into the power grid, there are several solving algorithms with distinct objective functions and computational constraints. When the objective is to minimize the load variance [45], quadratic programming (QP) seems to be the optimal solution, as it is topology independent but requires a high computational cost. When system peak shaving is of prioritization [46], Mixed Integer Non-Linear Programming (MINP) seems to be the most effective one as it can handle realistic three-phase unbalanced loads, but with the drawback of requiring (even higher) computational costs and is topology dependant. Future implementations will more than likely include multi-objective optimization models, but one thing in common for these algorithms is that a prerequisite for performing the load flow calculations is that the necessary network model is accessible to the aggregators. Usually these lay in the hands of the DSOs, which may or may not be hesitant to share them due to national security and individual integrity reasons. For the sake of these purposes, this has been assumed, but is nonetheless a politically imperative topic to dissect.

Since 2021, aggregators responsible for balance services have been active participants in the Swedish balance market and have been able to place bids with Svenska kraftnät and bypassing the balance responsibility party [47]. With that being said, current legislation does not allow for independent aggregation, since patrons are only allowed to have one electricity supplier per connection point, which means that aggregators would have to assume the role of a balance responsible party (BRP) to jointly operate the regulating power market (RPM) and thus be financially and legally liable for the entire electricity supply.

3.2.2 Load Disaggregation

Load disaggregation refers to the raw smart data conversion from household consumption into detailed classification of individual appliances. It is an essential tool for utilities to track their customers consumption patterns by extracting and analyzing their usage patterns. For the purpose of this thesis, a data set collected from the open source project Pecan Street was used to illustrate the electricity consumption by a household. The readings are from a residential home in Texas and were collected through intrusive monitoring, meaning the appliance dissagregation was performed by meter readings off of the specific appliances. This requires the home to be equipped with smart meters, which is true for all Swedish household customers since 2009. A new second generation of smart meters are being deployed with enhanced functionality, with all customers being equipped by the year 2025 [48].

The smart meter captures the instantaneous power consumption of the household through the superposition of each appliances power consumption. The instantaneous demand (P) of each appliance can be modeled by the variable $x_i(t)$ [W], t = 1,2,..., T where T is the duration of operation and $i \in M$ where M is the set of household appliances studied at the house. Then, the total power consumption of the house $p(t)$ is given by:

$$p(t) = \sum_{i}^{M} x_i(t) \tag{3}$$

The Issue of Fairness

Due to charging and system limitations, the issue of fairness appears when system capacity can't meet the desired demand. This is especially true in the context of full-scale implementation of demand response (see Section 3.1), since it is not obvious which customers should be prioritized and in which order. To tackle this, two fair scheduling processes are generally applied.

Equal Rotation: Equal Rotation scheduling assigns each EV simultaneously and in equal proportions in the prioritization scheduling, and performs this until Eq. 1 is satisfied for all users. The benefit of utilizing this scheduling is its simplicity and general fairness due to the weighted load distribution, which is preferred when energy demands are similar, but with the drawback of lacking the ability to unequally schedule events in the case where certain activities are more important than others (in the case of multiple flexible loads).

High Power Next: In a high power next (HPN) scheduling, users with the largest total power consumption will be prioritized first in the flexibility dispatch list. The HPN scheduling follows a queuing theory, and the ANM algorithm implementation is made by adjusting the prioritization for each iteration. In a real-life implementation this could be beneficial by utilizing a reward point system or bill credits. A reward point system could be provided by a third-party application provider, and bill credits may be assigned to the utilities implementing the DR program. Users may earn points based on the amount of energy saved by the flexible appliances during the DR scheduling. Furthermore, fairness issues occur in price and incentive-based DR methods when all charging demand is not fulfilled.

Although the individual mean price per kWh won't deviate much from the aggregated mean in the long term, studies have shown that psychological actions affects the requested charging schedule making it hard for the algorithm to perform fair ranking determinations [27]. Other prioritizations may also be implemented according to physical constraints, such as in the case with Level 3 supercharging where load power is gradually decreased in line with increased battery temperatures [49].

3.2.3 Dispatch Process

The dispatch process should follow a logical and minimalistic structure. The dispatch process is initiated with the EV aggregator executing the desired EV charging schedules for the given day by running power flows for the explicit (and accessible) area of the distribution network. With consideration to the scheduled demand, the aggregator can calculate the non-EV demand and set the available charging power limitations and forward this information to the EVs, assuming a constant network capacity. Following this, the EVs can validate whether these constraints violate the network boundaries, and whether it should re-evaluate its charging demand (on an hourly basis). This process is repeated until all participating EVs reach their demanded supply. The proposed dispatch process is depicted in Fig. 6.

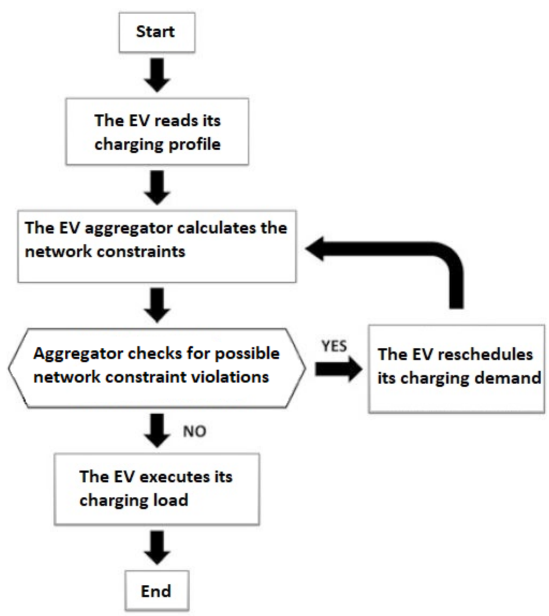

Figure 6: Flowchart for the proposed real-life dispatch process.

4 Methodology

In context to the proposed real-life implementation in the previous chapter, modifications have been made to adopt to the studied model. The model follows a centralized coordination structure, and in contrast to Section 3.2.3, instead of performing power flows to determine the network capacities based on the daily scheduled charging demand, network constraints have been set in advance based on an uncoordinated charging schedule. With the desired charging demands, the charging schedule is altered in real-time. Lastly, whether the desired charging demand is achieved or not is also variable which is inspected based on the case. The model is not necessarily depicting a real-life network, but rather one that is suitable and realistically dimensioned for a residential area excluding EVs.

4.1 Network Boundaries

According to Section 2.2, factual charging restrictions must comply with manufacturing requirements. As aforementioned, the charging current limit is bounded in the range of 8-16 A. For a three-phase 400 V (LL) system, the charging power for the n-th EV must thus be satisfied by 5.5 kW $\leq P_{t,n}^{EV} \leq$ 11 kW [5]. To ensure that the EV users don't experience range anxiety and can utilize regenerative braking, the charging requirement should be limited by 20% $\leq SoC_{t,n}^{EV} \leq$ 80%. To ensure that the energy demand is fulfilled, the following statement should be satisfied:

$$E_n = \eta_n \Delta t \sum_{t=\Gamma_n^s}^{\Gamma_n^e} P_{t,n}^{EV} = (SoC_n^e - SoC_n^s) C_n \tag{4}$$

where η_n denotes the charging efficiency (0.90), Γ_n^s and Γ_n^e denotes the start and ending charging time instances, and C_n denotes the battery capacity for the n-th EV. As stated in the introduction, the voltage constraints should be limited according to the EN50160 standard, and thus the voltage deviation limit should satisfy
0.9 pu $\leq V_{t,k} \leq$ 1.1 pu for bus k at time t. When EVs are charging from the grid, the load capacity for the feeder should not exceed its rated value. For feeder ι and charge-exclusive conventional load P_ι^{conv}, the feeder constraints can be specified by:

$$P_\iota^{conv} + \sum_{n=1}^{N} P_{t,n}^{EV} \leq P_{\iota,max} \tag{5}$$

[5] $P_{t,n}^{EV} = 3 \cdot V_{LN} \cdot I = \sqrt{3} \cdot V_{LL} \cdot I$

Alongside these limitations, no interference and optimal operations from the external MV grid has been assumed.

4.2 Data & Analysis

The EV charging load profiles have been obtained from the open source project Pecan Street [50], and have been extracted through load dissagregation conversion (see Section 3.2.2 and Eq. 3). For these purposes, this has thus already been done and is not of further concern. It contains two datasets for each day of the month, the household appliances and the EV chargers. The charging was conducted on a 3.7 kW level, and since Level 2 11 kW (230 V/16 A) charging is examined, an interpolation of the dataset has been made to correspond to the studied case. The data readings are minute values ($\frac{1}{60}$ Hz), and since the original battery sizes are unknown and the power ratings (and thus energy specifications) have been altered, the battery sizing have been adjusted accordingly. Fig. 2 depicts the aggregated demand for the dataset separated by the EV charging powers and the remaining appliances. Table 1 summarizes the relevant data utilised in this study.

EV	Arrival time	Departure time	Battery capacity [kWh][a]
1	01:40	03:47	25
2	18:39	03:18	30
3	00:16	04:09	50
4	19:42	01:46	75
5	21:23	00:01	35
6	16:24	09:10	55
7	01:58	06:01	60
8	20:56	05:30	65
9	18:26	22:22	70
10	18:10	07:59	100

Table 1: Extracted key parameters for the EVs.

[a]Rounded to the nearest multiple of 5.

4.3 LV Test Network with EVs

The LV network model represents a residential area with 10 households with accompanying EVs. The charging setup is three-phased 11 kV Level 2 charging and the EVs are represented as unidirectional battery units. It is a LV-radial, with an external 20 kV MV network grid and energized by a step-down transformer rated at 0.4/20 kV 40 kVA. It is based on [51], with an original rating of 150 kVA. Since the purpose of this study is to investigate the effects of non-dimensioned network overloads, 40 kVA was deemed appropriate in a non-including EV case. The power factor is assumed to be 0.95 and the specified voltage from the feeding point is 1.02 pu.

A schematic line-diagram over the low voltage test feeder is depicted in Fig. 7

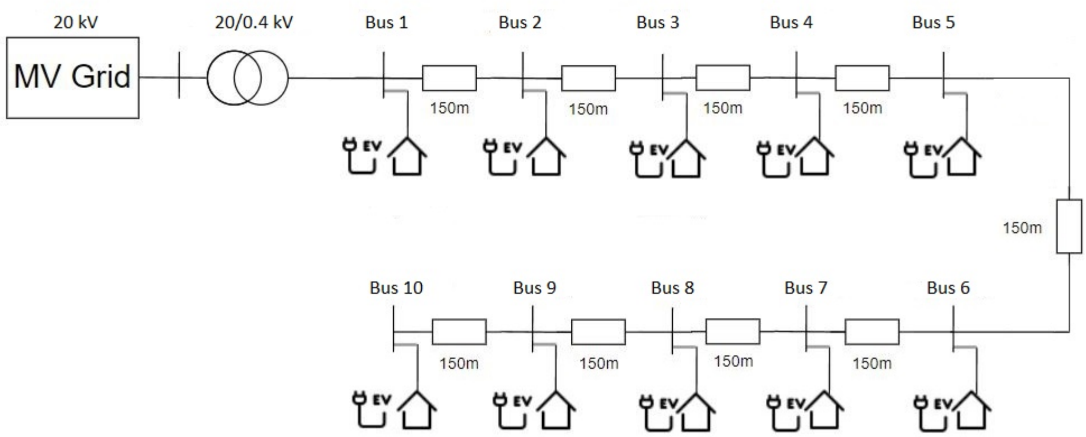

Figure 7: Single line diagram for the studied LV network.

The ratings and specifications for the model components are shown in Table 2-5.

Table 2: Transformer

	Value	[Unit]
Rating (S)	40	[kVA]
Resistance (R)	9.500	[mΩ]
Inductance (L)	55.863	[μH]

Table 3: VSC and Impedance Filter

	Value	[Unit]
Reactance (X)	1.333	[Ω]
Inductance (L)	4.2	[mH]
Grid Voltage	0.4	[kV]

Table 4: LV line

	Value	[Unit]
Length	0.15	[km]
Resistance (R)	0.346	[$\frac{\Omega}{km}$]
Reactance (X)	0.0754	[$\frac{\Omega}{km}$]
Ratio ($\frac{X}{R}$)	0.2179	
Line Resistance (R)	51.9	[mΩ]
Line Reactance (X)	36	[$\mu\Omega$]

Table 5: MV grid

	Value	[Unit]
Grid Resistance (R)	2.828	[Ω]
Grid Inductance (L)	9	[μH]
Grid Voltage	20	[MV]

Active Power Regulator and ANM Congestion Management Algorithm

The Active Power Regulator (APR) is represented as a Control Block in Simulink and consists of the ANM congestion management algorithm. It consists of a PI-controller with high gain (P) and integral part (I) for stationary error corrections, and control algorithms handling the charging start and ending times (T_{s_N} & T_{e_N}), and energy demand (E_N). The two main principles for the ANM algorithms functionality during controlled charging mode are:

- Excessive consumption on the feeder is assumed.
- It acts once the monitored quantity exceed it threshold value.

The PI controller has asymmetric output limits 0 and P_{max}. When $I_{measurements} > I_{max}$, the controller asks for a load curtailment. The flexibility dispatch determines an ordered dispatch list based off either power demand or in a uniform matter, based on the studied scheduling discussed in Section 3.2.2. A demultiplexer dispenses the appointed power curtailment to each affected EV according to the dispatch list. The inputs are the input dispatch list, individual EV charging powers, simulation time, network load sum as per Eq. 2, and corrective power, while the output are the individual curtailment powers. The charging process depends on the initial SoC and individual energy requirements, and the modelled EV chargers are controlled by their associated energy demands and their charging parameters based of Table 1. Based on the studied case, the APR is either active or inactive, and based on the studied case utilizes a specific dispatch prioritization.

A block diagram over the Central Controller is depicted in Fig 8, and Table 6 and **??** specify the block parameters and flexibility dispatch list respectively.

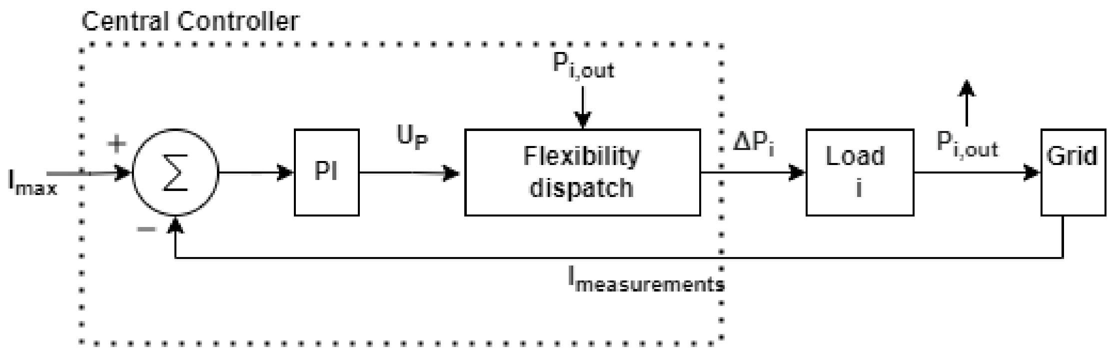

Figure 8: Block diagram of central control of active power consumption for congestion management. Flexibility dispatch decides in which order and magnitude the curtailment shall be distributed [16].

Table 6: Controller block parameters

	Value	[Unit]
Line current constraint ($I_{LN,RMS}$)	80	[A]
Grid voltage constraint ($V_{LL,RMS}$)	360	[V]
PI Gain (K_p)	100	
PI Integral (K_i)	10	

4.4 Case Study

In evaluating the methods presented, several test cases will be considered. For the LV network described in Section 4.3, three EV charging scenarios will be considered:

- Uncontrolled charging mode
- ANM controlled charging mode
- Tariff + ANM controlled charging mode

For all charging modes, the maximum allowed EV integration level is computed in an iterative manner in the network until a voltage or line violation occurs, without imposing any mitigation measures. In the second stage, the optimized (closed-loop) controlled charging strategy is compared with the uncontrolled (open-loop) and tariff-based (22:00-08:00) modes to assess its relative performance and effectiveness.

To evaluate the performance of the load control algorithm, several parameters will be analyzed. These are:

- Duration of load control
- Power reduction demand
- Cost benefit (hourly Time-of-Use (TOU) rates)

4.4.1 Load Scheduling and Control Algorithm

For these purposes, an instantaneous time-step (1min) has been implemented as it provides the best resolution. The scheduling list has been prioritizing EVs according to the Equal Rotation and High Power Next scheduling with the EVs as the sole flexible load. In the non-optimized uncontrolled real-time load control sequence, the EVs will only be addressed once during the cycle during times of low power reduction demand and will result in low distortion in owner comfort levels. On the contrary, if the power reduction demand is great, the EVs will be addressed several times during the cycle which may have an impact on the grid stability and owner comfort level. In this case, $t_{charge} = t_{arrival}$, meaning charging initiates once a user is registered at home. Over the course of time, this method may not provide an optimal solution in terms of load control when comfort levels and grid stability are of primary concern.

The optimized ANM version will have as an objective to smooth out the power peak demand and better dispatch the energy consumption throughout the day. As a consequence the grid stress and EV owner comfort level shall be better balanced than in the previous version. To implement this, a prerequisite is that required energy demand and time of available charging is known.

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5 Results

5.1 Maximum Market Penetration

According to the previously stated research, market penetration seems to have the biggest impact on the future of distribution grid reliability and it is thus of importance to evaluate the impacts on the distribution network for a given EV penetration level. As stated before, the transformer should not exceed 150 percent of its rated loading during excessive amounts of time to prevent premature ageing. In this network analysis, load control was shut off to showcase the disparity between the different charging modes. The transformer rating is 40 kVA (100%), and Fig. 9 depicts the maximum transformer loading that occurs during the simulations for rising proliferation rates for the studied cases without DSO intervention.

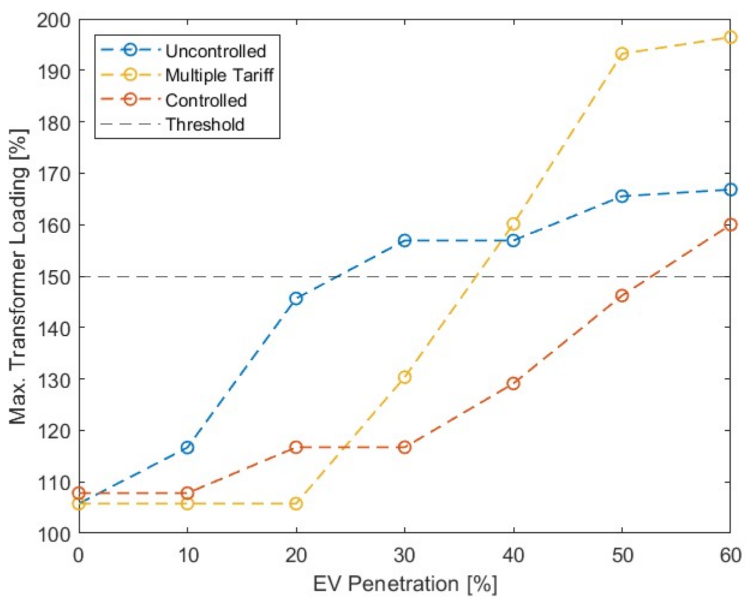


Figure 9: Max. transformer loading for rising EV proliferation levels.

For the uncontrolled, tariff-based and controlled charging modes, the percentage of EVs that can safely be integrated without imposing mitigation measures are 20-30 percent (24%), 30-40 percent (37%) and 50-60 percent (53%) respectively. Although the tariff-based charging strategy leads to the second lowest allowed EV integration percentage, it does lead to the highest peak load and curtailment duration (Fig. 16).

5.2 Power Demand and Available Capacity

The following results were simulated using a 50 percent EV integration level, meaning that five (5) EVs in the model are active, since this is the maximum (rounded) level possible using the controlled charging strategy without the need of network reinforcements or other measures of curtailment.

Uncontrolled charging

In the uncontrolled sequence, the EVs tended to predominantly charge in the late afternoon due to commuters returning home and in the morning hours prior to commuting as seen in Fig. 10. The requested demand in the afternoon provoked a intensified peak load which exceeded the technical limits of the network, and the DSO would need to curtail the excessive 25.5 kWh during 278 minutes (17:23-22:01) to avoid transformer overload. The morning EV load follows a more uniform charge distribution due to having a lower base load occurring, and tops out at a 100 percent (40 kW) of the transformer rating.

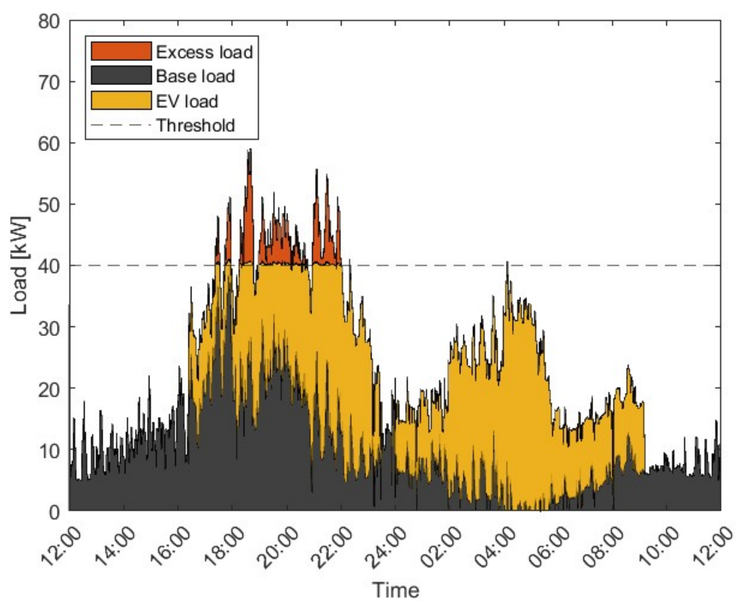


Figure 10: Load diagram for the uncontrolled charging sequence.

When curtailing excessive charging power the charging process is affected, and if the charging power is not compensated at another time instance the energy demand will not be satisfied. This is seen in Fig. 11, where all but EV 6 were able to meet their desired SoC. This has the potential to be solved by valley filling, in particular during the hours of 22:00-04:00 as seen in Fig. 10.

Worth mentioning is that the plots are normalized to their respective battery size, meaning EVs with larger capacities will take longer time to reach their desired SoC.

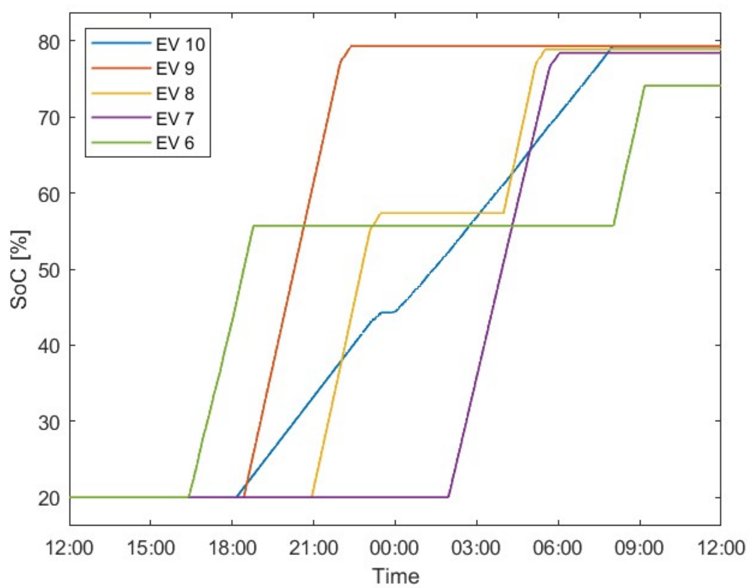


Figure 11: State of Charge diagram for the uncontrolled charging sequence.

Controlled Charging

In this sequence, the ANM algorithm is active and pursues to evenly distribute the EV load. Due to the fairness issues presented in Section 3.2.2, two schemes were simulated and assessed. The algorithm assumes the initiation charging times to be set and pursues to finish the charging prior to the owner commuting.

1. Equal Rotation

   In the Equal Rotation scheduling, it was assumed that all users experience an equal amount of power curtailment at all time instances.

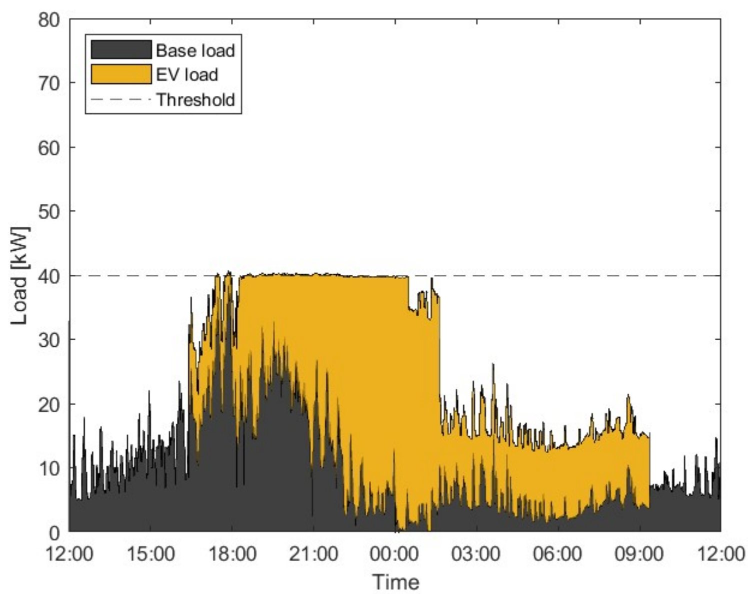


Figure 12: Load diagram for the RR controlled charging sequence.

   In this case, 94 percent of the requested charging demand was fulfilled without the need of DSO interference. Due to the relatively larger battery pack of EV 10, this scheduling proved to be not particularly fair in aggregate since it did not reach its desired SoC in time. For EVs in residential areas with more homogeneous charging patterns and charging demands this application may still prove to be viable. Also, in a more integrated context, this scheduling may prove to be more appropriate when household appliances are accommodated.

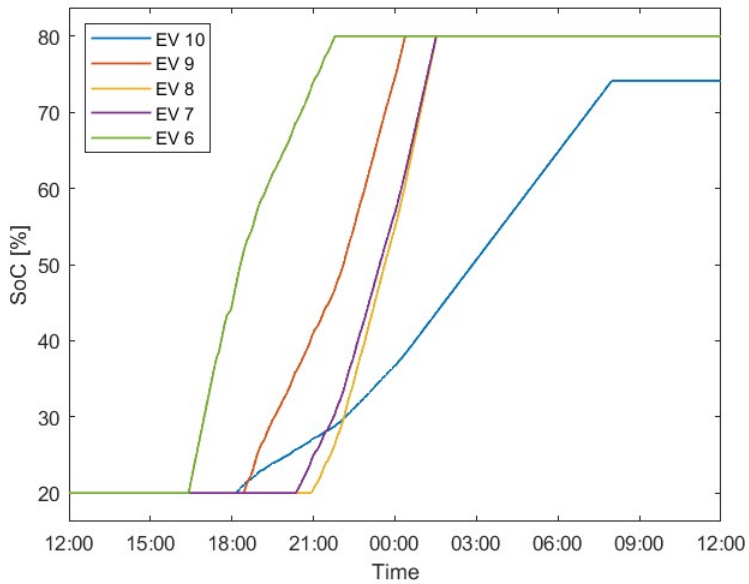


Figure 13: State of Charge diagram for the RR controlled charging sequence.

2. High Power Next

   In the High Power Next scheduling, it was assumed that users with the largest total power consumption will be scheduled first in the DR sequence. All of the requested demand was fulfilled without the need of DSO interference and within the requested time limits. All EVs except EV 10 were fully charged in the night and EV 10 was done with 5min left of its charging window. Thus, the High Power Next charging scheduling proved to be more efficient in this context in comparison to the Equal Rotation scheduling.

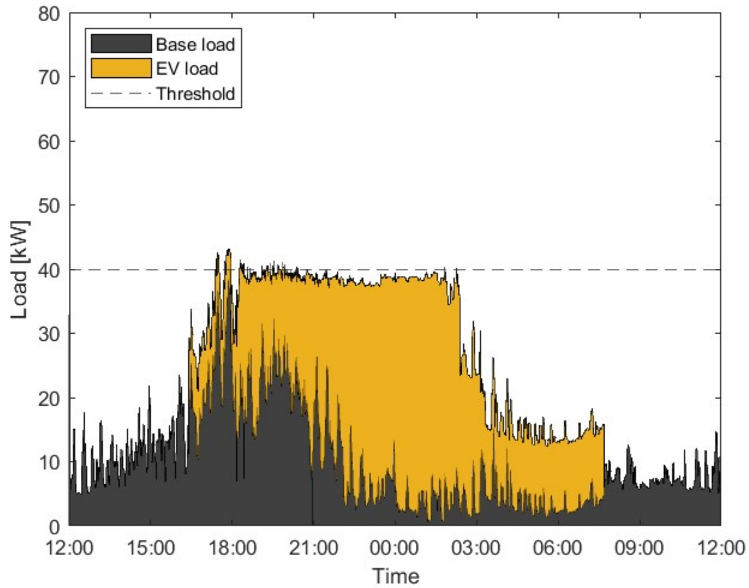


Figure 14: Load diagram for the HPN controlled charging sequence.

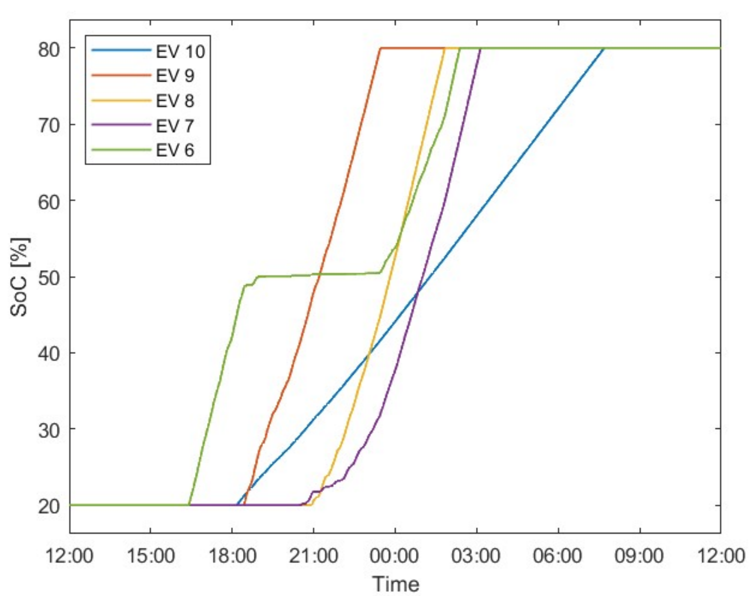


Figure 15: State of Charge diagram for the HPN controlled charging sequence.

Tariff Controlled Charging

For this network case, it was assumed that valley hours were occurring between the hours of 22:00-08:00 due to the low-price conditions, and that all EV owners adhered to this charging period. It showed to lead to the second lowest EV integration allowance, but accounts for the highest peak load as per Fig. 16. The reason for this is the peak occurring at 22:00 hours due to the initiation and assembling of tariff adherents with simultaneous charging in an uncoordinated scenario. In this case, the DSO would need to step in and curtail the EV load with 58 kWh for 210 minutes (22:00-01:30) to avoid transformer overload. This can be implemented using the ANM algorithm with HPN scheduling, which is showcased in Fig. 16 in yellow plotting.

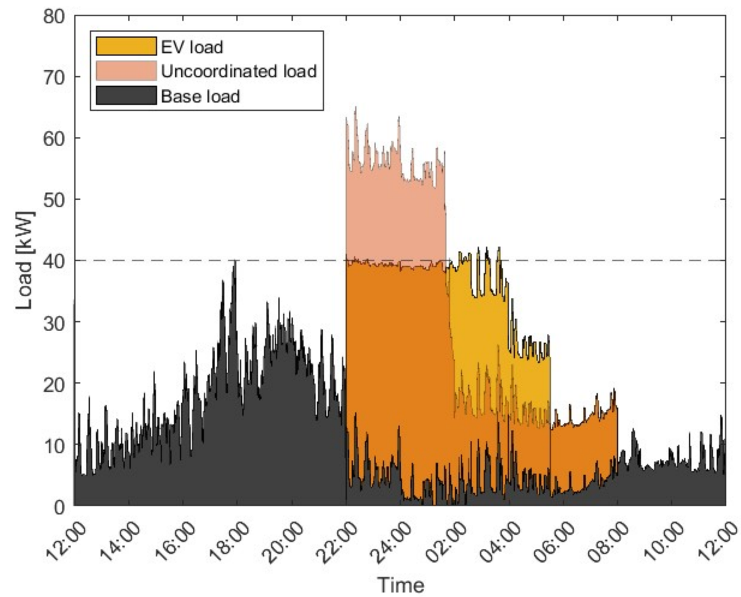


Figure 16: Load diagram for the tariff-based charging sequence (22:00-08:00).

Although it manages to limit the power below the network constraints, the time-price constraint at 08:00 prohibits 21 kWh of net charging energy to occur as depicted in Fig. 17. The reason for this is the remaining charge required by EV 10 which has a substantially larger energy requirement than the rest of the EVs (Table 1). As observed, the standalone tariff-based strategy does not correspond favorably with EV charging, as electricity prices do not consider local network loading.

Furthermore, the initial model does not allow for optimal valley filling by it self, but has the potential to be feasible in cooperation with the ANM algorithm.

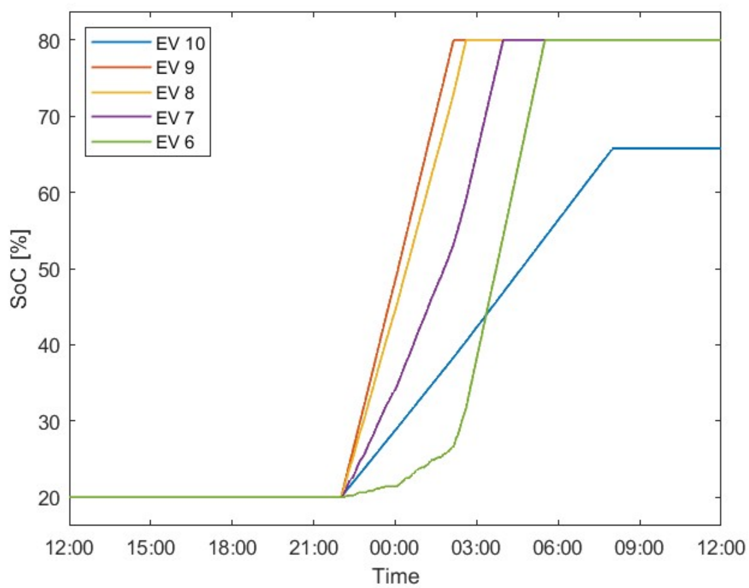
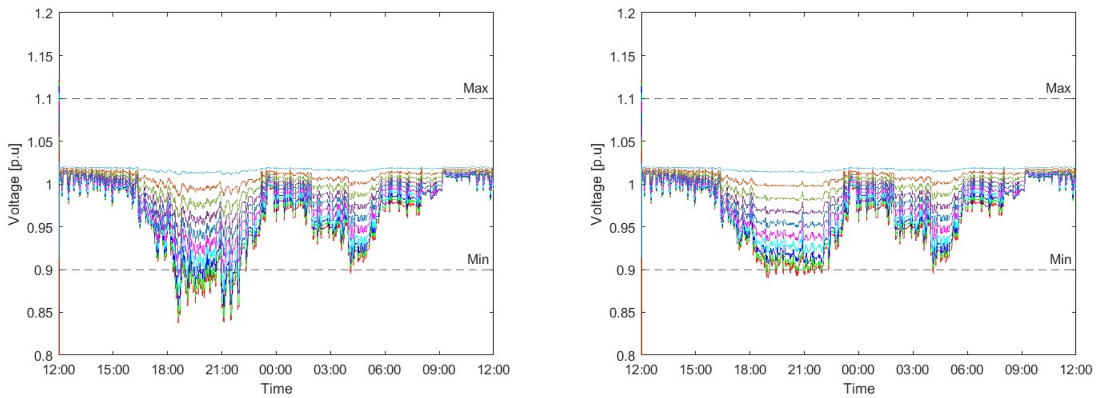


Figure 17: State of Charge diagram for the tariff-based charging sequence (22:00-08:00).

In comparing the charging costs, it was proven that the tariff-based scheduling with ANM algorithm was able to reduce the charging costs with 36 percent, adjusted for the energy loss.

5.3 Voltage Profiles

In gauging the impacts that the different charging modes incite on the node voltages in the LV network, the EV penetration level of 50 percent was utilized. For each scenario the voltages were registered, and since the greatest voltage drop occurs at node N, those loads were registered. The corresponding voltages are plotted in Fig. 18-20.



(a) Prior to Load Control.

(b) Post Load Control.

Figure 18: Voltage profiles for uncontrolled charging.

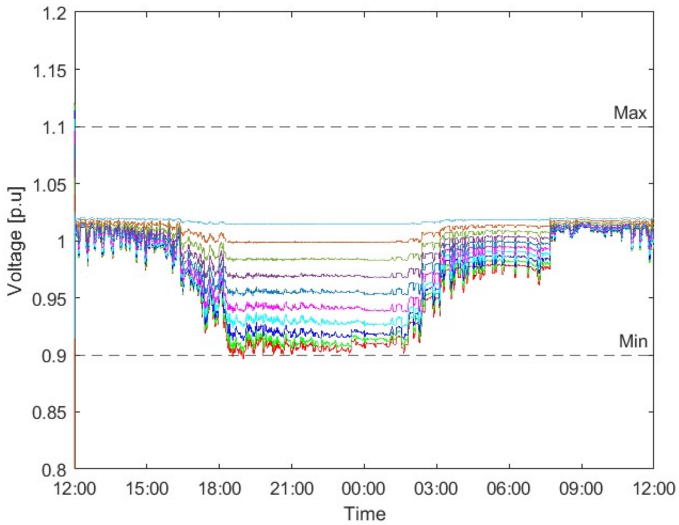
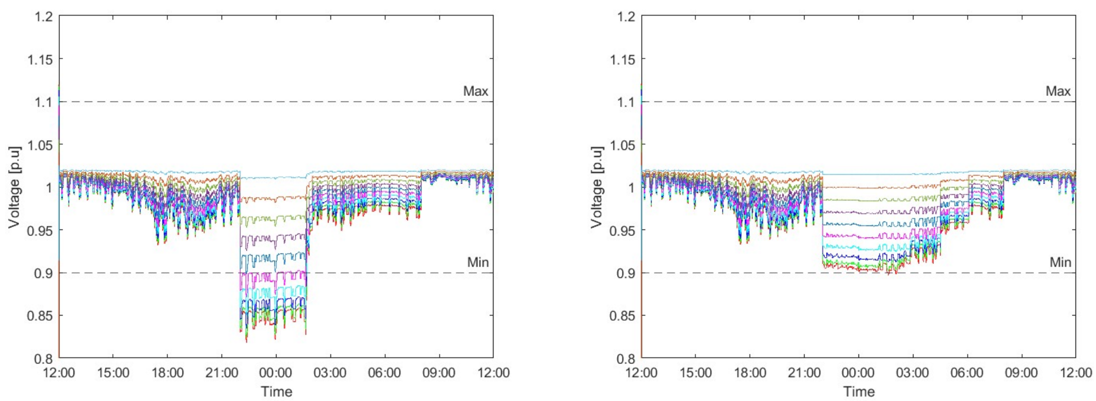


Figure 19: Voltage profile for controlled charging.



(a) Prior to Load Control.

(b) Post Load Control.

Figure 20: Voltage profiles for the tariff-based charging.

Voltage sensitivity for P variations increase in distance to the feeder transformer, and noticeable is that for the controlled charging sequence, the voltage is kept near the maximum allowed voltage deviation, which might raise concern in the long run. During normal grid operations the voltage generally does not surpass $\pm 5\%$ deviation.

6 Discussion and Conclusions

As an effort to present a feasible solution to congestion management in distribution networks, a proof of concept solution and algorithm evaluation has been presented. Load control and load management has the ability to bring advanced flexibility for the DSOs to operate and manage their network operations. By utilizing bounded constraints, operators are able to avoid complete load curtailments and feeder shutdowns to sustain customer comfort.

The power interaction between EV charging and power grids fall into two main categories, namely 1) uncoordinated charging and 2) coordinated charging. In the former, charging is operated regardless of the grid condition, and in the latter, charging is conducted through the establishment of intelligent communication links with the EV users to enable for better demand response in relation to the grid requirements. In the uncoordinated charge scheduling, further expansions of EVs is deemed inconceivable as the additional peak demand exacerbates the grid load and heavily overloads the transformers. Uncontrolled EV charging coordination is more prone to invoke negative impacts on the distribution network, as well as negatively impact the economic profitability of the EV aggregators. Explicit load control should only be utilized in emergency situations, since these mitigation actions would negatively impact the adaptation rate such as the customer comfort satisfaction. Without the ability to load shift to valley hours, as seen in Fig. 10, they won't be able to take advantage of the price arbitrage, and given the rising number of technical restriction violations expected with increasing EV penetration levels, DSO are left with only one possible solution: grid reinforcements.

In the optimized approach, by solely controlling the EV charging load, the ANM congestion management algorithm is able to level the power peak demand without affecting the grid nor customer demands. This could be further extended at the expense of other parameters, and to fully be implemented other constraints must be set in place. Thus, the tariff-based approach was investigated as an effort to cost-benefit the utilities and EV owners. Fig. 16 showcases the complication with this implementation without load control measures, as charging would likely be initiated with the tariff initiation and owners would concentrate at low-peak hours. Due to the bounded time-constraints, all the requested demand might not be satisfied as expected demonstrated in Fig. 17. With more adherents available in the distribution network, the deviation between the EV aggregator bought energy and the effective EV energy consumed would likely be greatly reduced.

The managing framework for load control implementation is imperative in its deployment. Although the centralized framework allows for optimal operations due to the unified management structure, the individual charging authority may be challenging to preserve. On the contrary, the decentralized framework is based on a price-signal mechanism with the independent EV users being individually able to determine their charging profiles, and is henceforth presumably more appropriate in obtaining a greater societal EV adaptation in the future. The open and flexible electricity markets of the US and European countries allows for market regulation of the electricity price which will encourage energy efficiency and demand response measures. The role and authority of EV aggregators should be further discussed as a deregulation would allow for these entities to exist and manage the EV charging and thus bargain with electricity retailers in the markets for profit generation, and may then become the energy aggregator for coordinated EV charging. In this context, the operating cost minimization would likely become the primary aim and the economic parameter is inclined to become the objective function in the mathematical expression for the charging optimization [44]. Regardless of the situation, an additional approach to this problem would be to incorporate other loads in the load control scheme. Flexible residential loads such as dishwashers etc. could be covered to further add flexibility at the customers convenience.

Since the individual energy consumption of residential houses may vary from day to day, and real-life grid structures are far more complex and include multiple feeders, the accuracy of the simulation model cannot be directly proven including the simplifications and assumptions made. Although depending on the energy requirements and available charging time, the control system could for example reduce the need for use of alternative charging stations notably. Customers might find it more convenient to charge their EVs whenever they find most suitable according to their work schedule outside of their home, and the extent of their tolerance for a less than fully charged battery and their driving regularity are factors which should be further investigated. In this implementation, dispatch is evident to fairness issues. Two fairness definitions of how the charging control could be interpreted was presented. Although there might be several more possibilities for how this term can be defined, these scenarios illustrated the ANM algorithms flexibility.

7 Future Work

Although the proposed ANM algorithm is able to sustain the power within the rated transformer rating, it is consistently running at 100 percent. Since line losses evolve in proportion with current square, this solution is not optimal in terms of loss minimization. Thus, of interest in future work would be to quantify how distribution network losses vary with different charging behaviours and control mechanisms. Future work should employ a more detailed cost function for the utility companies to incentive for implementation. Machine learning and multi-objective optimization models are imperative in predicting user's future energy demands and their behaviour, which would permit for more detailed pricing parameter determination. Furthermore, the proposed algorithm could be developed to take in consideration the demand curve a specific region should follow instead of purely limiting the the local demand. Ancillary services and V2G/PV integration measures may also add further flexibility and greater response in terms of frequency regulation and voltage and reactive power control. Lastly, future work should also involve three-phase load flow modeling to create the opportunity to look at phase-balancing of EV chargers, as well as harmonics and voltage deviations. Albeit not dissected in this thesis, these are all crucial topics related to the future integration of EVs in distribution networks and should be further studied.

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