MULTI-OBJECTIVE CHARGING SCHEDULING UTILIZING ELECTRIC VEHICLE LOAD MODELS

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ABSTRACT

MULTI-OBJECTIVE CHARGING SCHEDULING UTILIZING ELECTRIC VEHICLE LOAD MODELS

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Utilization of electric vehicle (EV) load models can improve the performance of smart charging strategies, which increase the reliability of the grid by harnessing the flexibility of EV loads. This thesis presents methods for utilizing EV load models in real-time stochastic charging control with single and finite system-time horizons. First, the drivers' load models are found with kernel density estimation. A single system-time horizon coordinated charging control algorithm is devised to ensure each EV is charged at least a critical amount given a feasible set of optimization constraints. The coordinated charging algorithm tackles the NP-hardness of single-deadline charging scheduling problems efficiently with a sorting algorithm utilizing the stochastic EV load models. Moreover, the single system-time horizon coordinated charging control algorithm is extended to a scheduling algorithm considering a finite system-time horizon. This approach utilizes the stochastic EV load models in a model predictive control based approach to decrease the complexity of stochastic online charging scheduling problem into a deterministic case. The scheduling algorithm makes assumptions about the future arrivals to the charging station, unlike the classical online EV charging scheduling algorithms, which optimize the load demand revealed at the current time but underestimate the load demand revealed in the future. Findings of the thesis work suggest the individual load models complement smart charging algorithms' decision process by improving the fairness of charging time allocation and extending the degree of knowledge of future random data for the scheduling algo-

rithm.

Keywords: Plug-in Electric Vehicles, Load Modeling, Smart Charging, Charging Scheduling, Electric Vehicle Grid Integration.

ÖZ

ELEKTRİKLİ ARAÇ YÜK MODELLERİNİ KULLANAN ÇOK AMAÇLI ŞARJ PLANLAMASI

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Elektrikli araç (EA) yük modellerinin şarj stratejilerinde kullanılması, EA yüklerinin esnekliğinden yararlanmaya olanak sağladığı için şebekenin güvenilirliğini sağlamak amacıyla geliştirilen akıllı şarj stratejilerinin performansını artırmaktadır. Bu tez, tek veya sonlu sistem zamanına sahip gerçek zamanlı stokastik şarj kontrolünde EA yük modellerinden yararlanan yöntemler sunmaktadır. Önce sürücülerin yük modelleri, çekirdek yoğunluğu tahmini yöntemi ile bulunmuştur. Tasarlanan tek sistem zamanı ufuklu koordineli şarj kontrol algoritması ile her bir EA'nın uygun optimizasyon kısıtlamaları seti verilmesi şartıyla en az kritik bir miktarda şarj edilmesini sağlamaktadır. Bu algoritma, stokastik EA yük modellerini kullanan bir sıralama algoritması sayesinde tek zaman adımlı şarj çizelgeleme problemlerinin hesaplama yükü problemini verimli bir şekilde ele almaktadır. Ayrıca tek sistem zaman adımlı koordineli şarj kontrol algoritması çözümü, sonlu zaman ufkuna sahip çizelgeleme algoritmasına genişletilmiştir. Bu yaklaşım, stokastik çevrimiçi şarj çizelgeleme probleminin karmaşıklığını deterministik bir duruma indirgemek için model tahmine dayalı bir yaklaşımda stokastik EA yük modellerini kullanmaktadır. Çizelgeleme algoritması, mevcut zamanda ortaya çıkan yük talebini optimize eden ancak gelecekte ortaya çıkan yük talebini dikkate almayan klasik çevrimiçi EA şarj programlama algoritmalarının aksine, şarj istasyonuna gelecekteki varışlar hakkında varsayımlarda bulunmaktadır. Tez çalışmasının bulgularına göre bireysel yük modelleri, şarj süresi tahsisinin adil-

liğini geliştirerek ve çizelgeleme algoritması için gelecekteki rastgele verilerin bilgi derecesini genişleterek akıllı şarj algoritmalarının karar sürecini iyileştirmektedir.

Anahtar Kelimeler: Şebekeye Bağlanabilen Elektrikli Araçlar, Yük Modelleme, Akıllı Şarj, Şarj Planlama, Elektrikli Araç Şebeke Entegrasyonu.

To my family.

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ALGORITHMS

ALGORITHMS

CHAPTER 1

INTRODUCTION

The global transition of the light vehicle fleet to electric vehicles (EVs) advanced significantly over the last decade, underpinned by technological advances, green energy policies, and supportive government incentives. However, uncoordinated penetration of EVs due to the electrification of the transmission sector prompts overloadings and low voltage violations that the existing power grid cannot manage. This thesis is concerned with the electric vehicle charging problem and proposes charging control methods utilizing EV load models as a smart charging solution for workplace charging stations.

To understand the relevance of this work, it is necessary to explain the emerging changes in the power system and the political reasons behind this transformation first. The following subsections introduce a political and technical background of the EV charging problem.

1.1 International Agreements on Climate Change

In 2015 at the United Nations Climate Change Conference (COP 21), representatives of the 196 attending parties of the United Nations Framework Convention on Climate Change (UNFCCC) reached a consensus on the Paris Agreement to keep the rise in global temperatures to well below 2°C and limit the temperature increase to 1.5°C above pre-industrial levels by 2050 [1]. The Paris Agreement is considered a landmark in the multilateral climate change process since, for the first time, a binding agreement brings nations into undertaking efforts to combat climate change problem.

On Earth Day (April 22) in 2016, 174 of these countries signed the Paris Agreement in New York and began adopting it within their legal systems.

The key aspects of the goals adopted by the Parties at the COP 21 are summarized as follows:

- The long-term temperature goal seeks to limit the global temperature increase to well below 2°C while pursuing efforts to limit the increase to 1.5°C.
- All Parties shall pursue domestic measures to achieve a nationally determined contribution (NDC) and communicate their NDCs every five years to provide clarity and transparency.
- According to global peaking and climate neutrality goals, Parties aim to reach global peaking of greenhouse gas emissions (GHGs) as soon as possible to achieve the long-term temperature goal while recognizing that peaking will take longer for developing country Parties.
- Parties are to enhance understanding, action, and support for improving climate resistance and adaptation capability against climate change's adverse effects, protecting food production from getting harmed.
- Parties of the Agreement are to stabilize the financial flow for the low GHG and climate persistence development to the best of their capability. The Paris Agreement reaffirms the obligations of developed country Parties to support the efforts of developing country Parties to build clean, climate-resilient futures.

Additionally, The Green Deal declared by the European Union (EU) in December 2019 sets further targets to make Europe carbon neutral by 2050 and reduce greenhouse gas emissions by 55% compared to the 1990 levels by 2030 [2].

1.1.1 Turkey's Ratification of the Paris Agreement and Green Deal Action Plan

Although Turkey signed the Paris Agreement on April 22, 2016, the ratification of the agreement entered into force almost five years later by the Official Gazette (numbered 31621) dated October 7, 2021, with the article named "The Law Regarding the

Approval of the Paris Agreement" ("Paris Anlaşmasının Onaylanmasının Uygun Bulunduğuna Dair Kanun"). The action plan released by the Turkish Republic Ministry of Trade, the Green Deal Action Plan of Turkey (Yeşil Mutabakat Eylem Planı), sets out the following targets:

- Harmonizing with the EU's environmental regulations,
- Usage of a cleaner energy supply model; allocating 1 GW capacity for new solar and wind power plants each year until 2027,
- Enabling green investment through financing; transmission of a green farming policy; transforming into a sustainable and intelligent transportation system.

The ratification of the Paris Agreement and Green Deal Action Plan by the Turkish Parliament signifies that Turkey will become more effective in taking steps in accordance to fulfilling its obligations concerning the global climate crisis and achieving its goals in accordance with the EU's goal of climate-neutrality as of October 2021.

1.2 Changes in the Power System Operation

Targets of the Paris Agreement and the Green Deal Plan dictate comprehensive decarbonization of the energy sector [3]. Significantly greater penetrations of variable renewable energy (VRE) resources and increased electrification of end-use sectors such as heating, industry and transport are two key elements that prove decisive for the decarbonization goals [4, 5].

According to International Renewable Energy Agency (IRENA), the contribution of renewable energy sources to the global annual electricity generation needs to increase from 25% today to 86% to meet the 2050 goals. Around 70% of this 86% is expected to be supplied from VRE sources, accounting for 60% of the total annual electricity generation. On the other hand, reducing fossil fuel dependency through electrification, with the transportation and heating sectors being the most notable examples, is expected to double the electricity consumption considering all energy applications by 2050 [5].

With the increased VRE penetration and electrification following the Paris Agreement goals, new concepts such as the smart grid paradigm, flexible loads, and distributed energy resources (DERs) have been introduced into the power system. The following subsection gives an overview of the traditional power system and the expected changes to form the modern power system, which expands the flexibility for a safer adaptation of DERs.

1.2.1 The Traditional vs. Modern Power System

The traditional power system was designed to follow the demand by generating electricity at bulk generating units to be more economical. Electricity is delivered to the consumers in a top-down approach through the transmission and the distribution grid over long distances, as depicted in Figure 1.1.

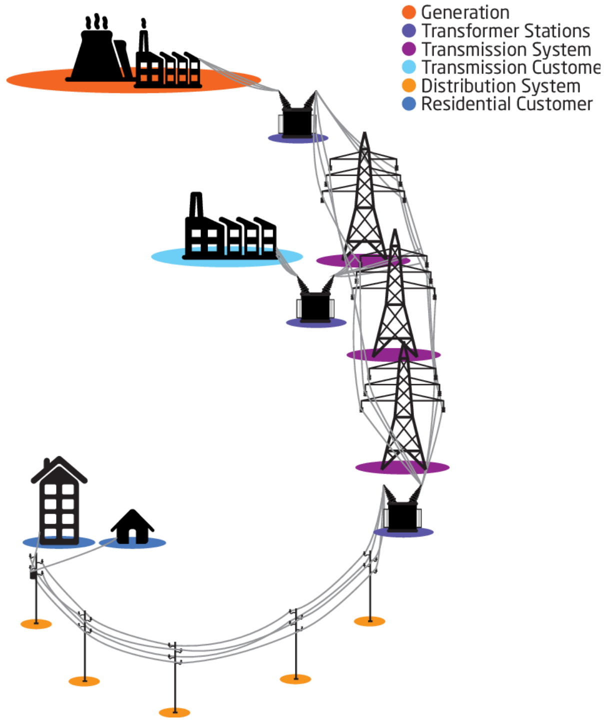


Figure 1.1: The traditional power system. Source: [6].

With the conventional power system technology, it is not possible to store energy in large orders; therefore, flexibility has been typically harnessed on the generation side. Consumers' energy demands for the next day are forecasted, and generator units are scheduled accordingly by the Transmission System Operator (TSO). In this paradigm, the electricity supply must match the demand at all times. The TSO resolves the imbalance (if any) between the generation and consumption to secure the grid's stability through the ancillary service markets.

Conventionally, ancillary services are provided by hydropower or fossil-fuel-powered units that provide energy from a portion of their capacity but have additional unused capacity. It is important to note here that the majority of the fossil-fuel-powered plants need to be replaced with renewable energy resources to meet the decarbonization goals of the Paris Agreement. Therefore, new sources for ancillary services in favor of the agreement must be found.

In the modern grid structure, new elements, commonly referred to as DERs or flexible resources, are introduced at the distribution level. Consequently, it is primarily the distribution system operator's (DSO) responsibility to resolve the problems arising due to the integration of these technologies. Examples of the DER technologies include EVs and heat pumps as consumers and wind turbines, small-size generators, and photovoltaic (PV) units as producers.

The modern smart grid structure can be seen in Figure 1.2. The flow of electricity is not only from large generating units to consumers through transmission and distribution systems, but there is also intermittent electricity generation by the DERs at the distribution level. Furthermore, the smart grid structure contains an extensive information and communications technologies (ICT) infrastructure, which enables the communication and control between the system actors.

In order to address the new challenges arising from the high penetration of VRE resources and increased load demand due to electrification, consumers are expected to become both producers and consumers of electricity, i.e., *prosumers*. In this context, flexibility is harnessed not only on the supply side but also on the demand side, an approach referred to as *demand-side flexibility*. The consumers become active participants in the grid operation by providing ancillary services to the system operators through aggregators.

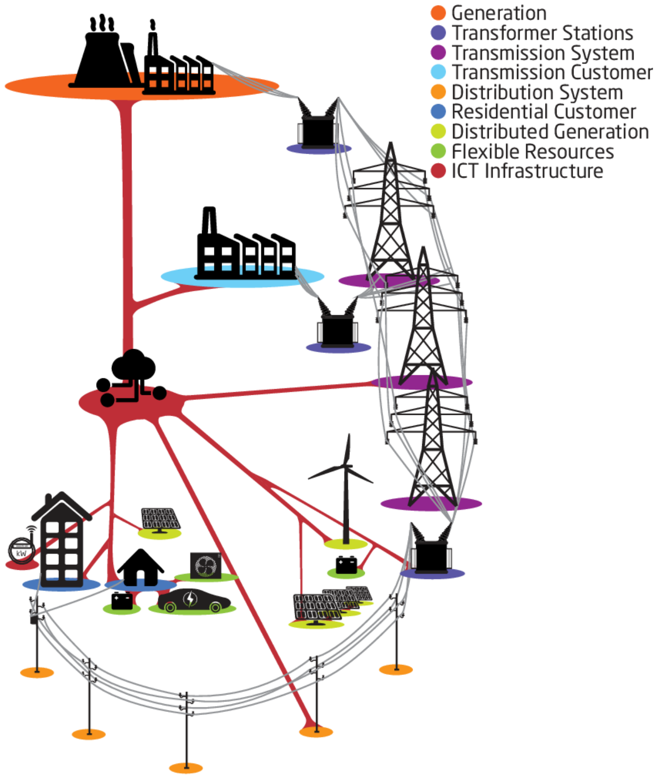


Figure 1.2: The smart grid power system. Source: [6].

An *aggregator* is a market participant that manages a pool of consumers, producers, prosumers,or any mix thereof as a virtual power plant (VPP) to act as a single entity when engaging in wholesale and retail markets or selling services to the system operator [7, 8]. Aggregators deliver essential benefits to the smart grid operation [6, 8], including

- Providing asset management service to the end customers from industrial, commercial, and residential sectors to have a reliable and cheap service,
- Providing local flexibility, load shifting, and ancillary services to the system operators by acting as VPPs,
- Facilitating ICT and control infrastructure for DER owners for these services,
- Securing some certainty of service delivery and taking legal responsibility towards the system operators.

Aggregators are essential agents to increase the system's flexibility as they serve as an intermediary that exempts the higher-level control agents (TSO/DSO) from direct interaction with the massive number of DERs, which is impractical. The next chapter briefly discusses the flexibility enablers of the smart grid paradigm and demand-side flexibility technology mapping of end-use sectors.

1.2.2 Power System Flexibility for the Energy Transition

The growth of the power demand due to electrification creates challenges in covering the peak demand and increasing ramping requirements and aligning the supply and demand, given a variable generation mix. Also, the variability and uncertainty introduced on the supply side by the high penetration of VRE require sources of flexibility through demand-side management and supply-side solutions [9]. These challenges call for flexibility to be increased and harnessed through a portfolio of technologies across all parts of the system [10], which could be grouped under five key technical groups:

1. Supply-side flexibility, e.g., flexible power plants,
2. Demand-side flexibility, e.g., demand response, sector coupling.
3. Storage systems, e.g., hydrogen storage units, batteries,
4. Grid infrastructure, e.g., transmission expansion,
5. Improved operation, e.g., hydro-thermal co-optimization methods, market and control designs with new agents such as aggregators.

Figure 1.3 lists the power system flexibility enablers associated with these technical groups. Among these enablers, sector coupling is considered both supply and demand-side flexibility enabler as it takes place only if the electrified resources (electrification of heat or transport, e.g., power-to-heat, power-to-gas, and smart charging of electric vehicles) are used in a way that favours VRE integration.

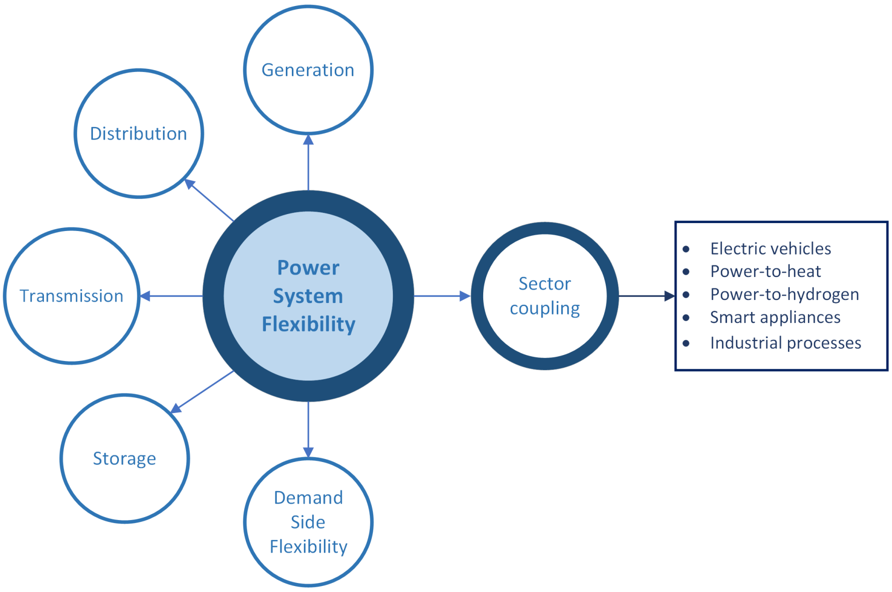


Figure 1.3: Power system flexibility enablers in the energy sector.

Sector coupling resources can be combined with smart appliances in residential, commercial, and industrial applications. The compatibility and suitability of the *sector coupling* solutions vary depending on the end-use sectors analyzed, namely industrial, commercial, or residential. For example, the potential for gaining flexibility from hydrogen production is more significant for the industrial sector, whereas direct electrification with VRE sources is a cheaper alternative for residential and commercial buildings. Table 1.1 maps the compatibility and suitability of demand-side technologies to the end-use sectors [3].

Sectors	Industrial	Commercial	Residential
Electric vehicles	○	●	●
Power-to-heat	●	●	●
Power-to-hydrogen	●	○	○
Smart appliances	○	●	●
Industrial processes	●	○	○

● Flexibility solution would be competitive/suitable in that end-use sector,

○ Flexibility solution is unlikely to be competitive/suitable in that end-use sector

Table 1.1: Demand-side flexibility technology mapping of end-use sectors

1.3 Electrification of the Transportation Sector

Electric vehicles are defined as vehicles whose driving torque is produced by motors. EVs can use electric motors or traction motors for propulsion and can be powered by electricity from an off-vehicle source or self-contained by a generator that converts fuel to electricity [11].

According to the 2021 issue of Global EV Outlook, which is annually published by the International Energy Agency (IEA) that identifies and discusses recent developments in electric mobility across the globe, the transportation sector has the highest reliance on fossil fuels of any sector as it accounts for 37% of CO_2 emissions from end-use sectors [12]. Initiatives countries have taken following the Green Action Plan encourage shifts to the less carbon-intensive travel options and energy efficiency measures to reduce the carbon intensity of transport modes. Accordingly, the electrification of the transportation sector will accelerate the wide-scale adoption of EVs [13]. In 2021, electric car sales more than doubled to reach 6.7 million, representing close to 9% of global car sales. The number of electric cars on the world's roads had reached 16 million at the end of 2021, whereas there were only about 17,000 EVs in 2010 as depicted in Figure 1.4.

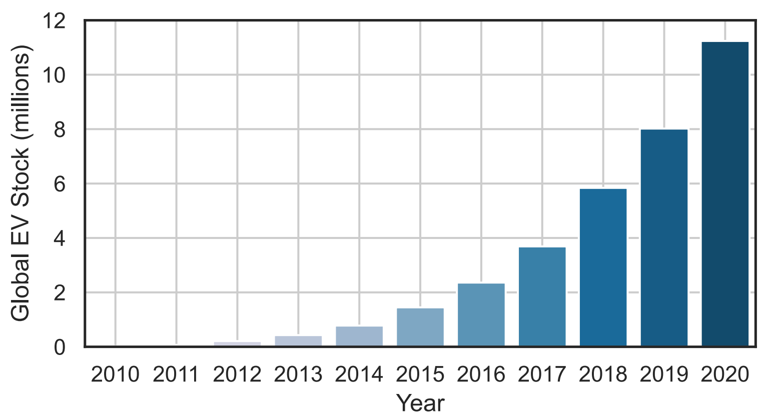
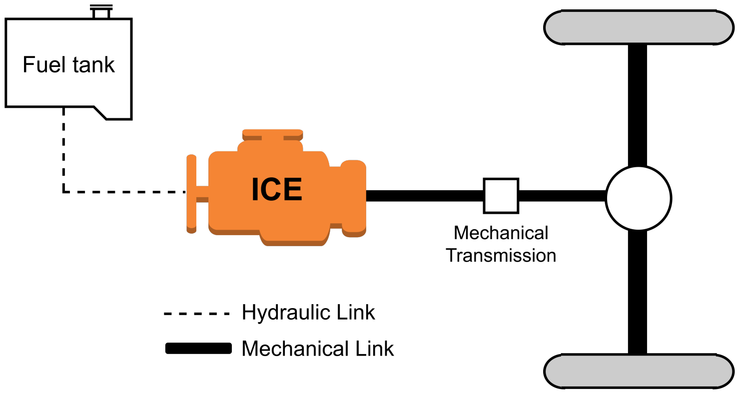
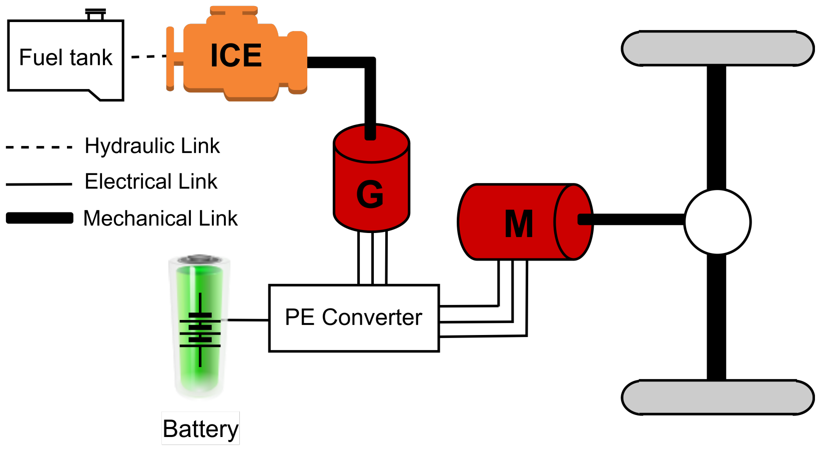


Figure 1.4: Global electric vehicle stocks announced by the IEA (2010-2020).

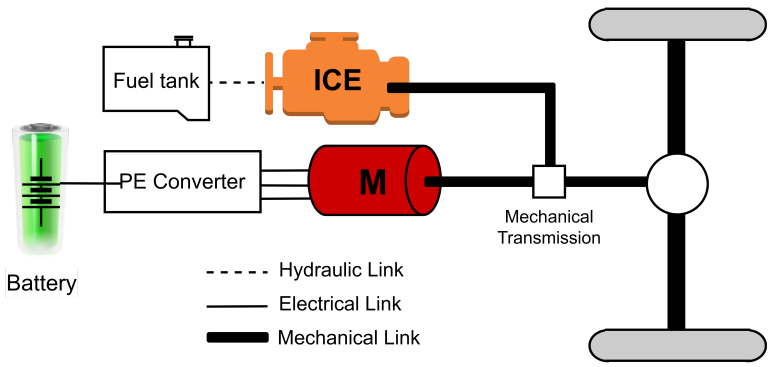
Regarding the electrification of the vehicles, there are several types of EVs in the market that are alternatives to internal combustion engine (ICE) vehicles [14]. Figure 1.5 illustrates the propulsion systems of the most relevant vehicle architectures. Battery



(a) Internal combustion engine vehicle.

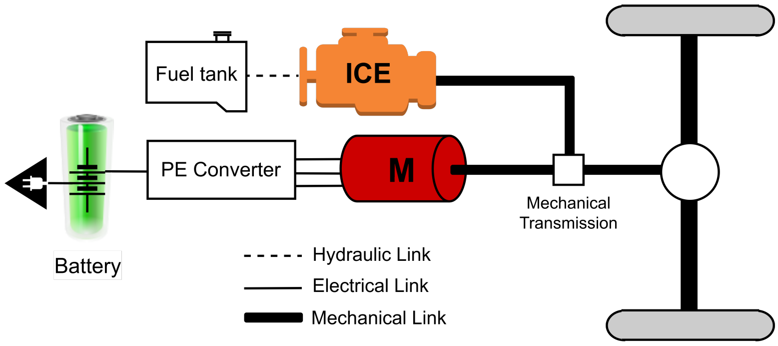


(b) Series hybrid electric vehicle.

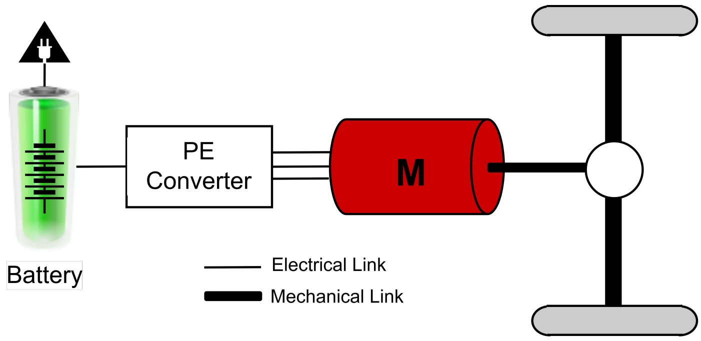


(c) Parallel hybrid electric vehicle.

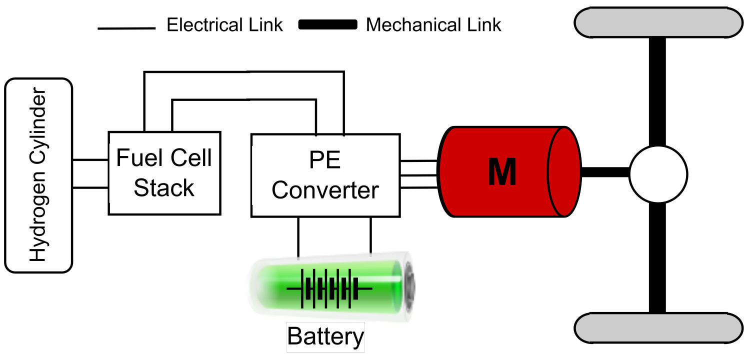
Figure 1.5: Propulsion systems of most relevant vehicle architectures.



(d) Plug-in hybrid electric vehicle.



(e) Battery electric vehicle.



(f) Fuel cell vehicle.

Figure 1.5: Propulsion systems of most relevant vehicle architectures (cont'd).

electric vehicles (BEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEV) are the main types of EVs [15].

Batteries of HEVs cannot be plugged into the grid to charge the battery. Instead, the battery is charged through regenerative braking and the ICE. Figures 1.5b and 1.5c show the propulsion systems of series and parallel HEVs, but the series-parallel hybrid vehicle and the complex hybrid vehicle architectures also exist [15]. PHEVs (Figure 1.5d) can be plugged into the grid and charged fully. Also, PHEV batteries can be charged by regenerative braking, which extends the driving range. A BEV (Figure 1.5e is a type of EV that exclusively uses chemical energy stored in its rechargeable battery packs, with no secondary source of propulsion, e.g., hydrogen fuel cell or internal combustion engine. FCEVs (Figure 1.5f) are fueled with hydrogen gas stored in a tank on the car, where energy stored as hydrogen is converted to electricity by the fuel cell. FCEVs can fuel in minutes and have a driving range over 450 km. However, the market for them is quite limited due to the limited and expensive hydrogen infrastructure [11], which makes plug-in electric vehicles (BEVs and PHEVs) the number one candidate for the electrification of the transportation sector.

In this thesis, plug-in electric vehicles are referred shortly as EVs.

1.3.1 Electric Vehicle Charging Problem

Electric vehicles are high-power consumers in the presence of uncoordinated penetration that the grid should supply. For example, the power consumption of the BMW i3 (BMW i3s 120 Ah, Model 2022) is 14.7 kWh per 100 km, whereas the average daily electricity purchased by residential customers in the United States is approximately 10.7 kWh [16]. The widespread adoption of EVs prompts higher peak load demands and ramping requirements that the existing power grid cannot manage [17]. The local distribution grid is affected negatively by uncontrolled EV charging in terms of its voltage profile, power loss, grid unbalance, reduction of transformer life, and harmonic distortion. Thus, ubiquitous research studies address these problems by proposing various smart charging methods by investigating the EV charging problem from different aspects.

Advances in EV charging system design, hardware, monitoring, and control, which are collectively referred as *smart charging strategies*, are utilized for a safer adoption of EV loads. Such strategies demand-side flexibility by optimizing the charging process according to grid constraints, local availability of VRE resources and customers' preferences.

1.4 Smart Charging

Smart charging is crucial for large-scale charging facilities, especially those with weak grid connections. Smart charging can minimize the grid congestion (by shifting charging times from the morning and evening peaks) and the charging cost by following VRE availability and avoiding charging when prices are very high due to scarcity events in the grid. In addition, V2G technology enables selling energy back to the grid when it is most needed or expensive [3].

According to the existing literature on smart charging control algorithms, EV charging solutions can be grouped with respect to EV charging methods, charging direction and control levels, charging environment, and charging control architectures. Figure 1.6 summarizes the classes of EV charging solutions.

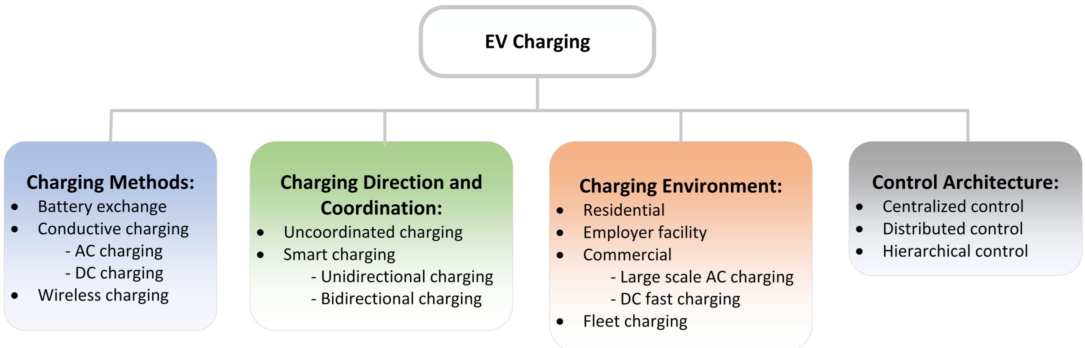


Figure 1.6: Classification of EV charging solutions.

The first classification of EV charging solutions investigates the EV charging problem from a technical level, i.e., the physics of the charging process, charging protocols, and the safety, communication, and generic standards. Battery exchange, conductive charging, and wireless charging are the three main charging techniques, of which the latter two are for PHEVs [18]. This thesis, and an overwhelming majority of the

EV charging control literature, deals with the conductive charging methods. Several charging techniques exist for conductive charging. In this context, organizations such as IEC, SAE, IEEE, and CHAdeMO have established many AC and DC charging mode standards [14], as explained in detail in Chapter 2.

Secondly, charging solutions can be classified as uncoordinated charging, where EVs are charged at maximum power when they are plugged into the grid, and smart charging [19]. The smart charging strategies can be further divided into unidirectional (also called V1G) and bidirectional charging (vehicle-to-home (V2H) and vehicle-to-grid (V2G)).

Another classification is based on the location of EVSEs as the benefits and control challenges of residential, commercial, and fleet charging applications vary substantially. For instance, residential EV loads have the most flexibility [20] in charging time. Fleets of vehicles owned by a single organization, such as school buses, taxis, and post cars, have more advantages in V2G as they can be aggregated easily [11]. Commercial AC charging stations have resource allocation problems [21, 22], and DC fast-charging stations have higher grid impacts [23]. Thus, charging solutions are designed to maximize the profit while minimizing the grid impact, considering the peculiar benefits and setbacks to these environments.

Finally, EV charging solutions can be classified according to their control schemes, i.e., based on whether decisions on a group of EVs are made by a single entity (centralized control), by individual EVs (decentralized control), or in a tree structure of aggregators (hierarchical control) [24].

1.4.1 Smart Charging System Entities

Smart charging applications requires coordination and communication between charging system entities, i.e., EV, EVSE, and third-party operators, which are one or a combination of e-mobility and energy entities listed below [25]. The ecosystem entities exchange information and control signals through communication protocols to manage the time and speed of charging (See Chapter 2.2.). Front-end protocols link EV with EVSE, while the-back end protocols link EVSE with CPO and third-party operators with each other.

the communication protocols between the EV and the charger

Charge point: Charging location containing one or more EVSEs.

Energy Management System (EMS): Smart energy management system that monitors and optimize energy consumption and generation of a small local system such as smart homes and smart buildings.

Electric Mobility Service Provider (eMSP): The entity holding a contract with EV owners for services related to charging.

Charge Point Operator (CPO): The central system entity which operates and manages charge points.

Energy Supplier: The entity selling electricity to consumers.

Balance Responsible Party: An entity which is financially responsible for the real-time balance of supply and demand.

TSO/DSO: Transmission/Distribution system operator.

Aggregator: An entity responsible for aggregating DERs to provide power system services to third-party entities (See Section 1.2.1.).

Smart chargers connect EVs to the grid facilitating the additional hardware and software for exchanging information and control signals in order to manage the time and speed of charging (i.e., power rate). Additionally, a smart charger with V2G capability can switch the direction of charging by allowing EVs to sell energy back to the grid. Both charging technologies ensure EVs are charged to meet the EV owners' requirements, usually set by the EV owner through a mobile application [20].

Smart charging stations are advantageous at locations providing the latent flexibility of charging allows managing the charging time and rate without violating the EV users' charging requirements; see Table 1.2. Residential and workplace charging locations where EVs are routinely parked for an extended period provide the necessary flexibility for smart charging. DC fast charging, which supplies around 80% of

Table 1.2: Characteristics of typical light-duty EV charger locations.

		Residential	Work	Commercial	
Locations		Garages, street parking	Parking lots	Malls, filling stations	DC FC Stations
Parking duration		Overnight	Work hours	2-4 hours	Minutes
Charging Rate	< 22 kW	Applicable	Applicable	Applicable	Not applicable
	50-150 kW	Not applicable	Applicable with limitations	Applicable with limitations	Applicable
	> 150 kW	Not applicable	Not applicable	Not applicable	Applicable
Smart charging		Applicable	Applicable	Applicable with limitations	Applicable with limitations
V2G		Applicable	Applicable	Not applicable	Not applicable

● Applicable ● Applicable with limitations ● Not applicable

recharge in 30 min for a 135-160 km range, is unsuitable for load shifting or V2G; however, it requires some communication with the grid and control for charging efficiency and minimizing the grid impact.

1.5 Thesis Outline and Contributions

This thesis deals with the electric vehicle charging problem, in particular, AC charging control, and proposes a coordinated charging algorithm and a multi-objective charging scheduling method utilizing EV load models as a smart charging solution for private workplace parking lots. The rest of the chapters with the corresponding contributions are summarized as follows:

Chapter 2 provides a cyber-physical overview of the smart charging ecosystem, alleviating confusion among commonly used EV charging standards and protocols by stating where these terms are applicable. It explains common EV charging terms, charging modes/levels, and applied codes and standards for conductive charging systems, followed by the front-end and back-end communication protocols enabling smart charging.

Chapter 3 presents a method based on Kernel Density Estimation to develop the individual load models of EV users while keeping the identity of the drivers for coordinated charging strategies. This chapter considers the necessity of modeling the EV drivers separately for coordinated charging by investigating the random variables describing the individual EV drivers. A coordinated charging control algorithm with a single system-time horizon is devised to ensure each EV is charged at least a critical amount given a feasible set of optimization constraints. The coordinated charging algorithm tackles the NP-hardness of charging scheduling algorithms by sorting the values assigned to EVs using the stochastic load models.

Chapter 4 studies EV charging scheduling problem for workplace charging stations. The single system-time horizon coordinated charging control algorithm is extended to a multi-objective scheduling algorithm considering a finite system-time horizon. The proposed online charging scheduling algorithm makes assumptions about the future arrivals to the charging station. Therefore, unlike the classical online EV charging scheduling algorithms, which optimize the load demand revealed at the current time but underestimate the load demand revealed in the future. EV load models are utilized in a model predictive control based approach to decrease the complexity of the stochastic online charging problem into a deterministic case.

Finally, Chapter 5 summarizes the results and concludes the thesis with a discussion of the findings, limitations of this work, and future work in this research domain.

CHAPTER 2

INTEGRATION OF ELECTRIC VEHICLES TO THE SMART GRID

This chapter explains common EV charging terms, charging modes/levels, and applied codes and standards to charging systems. First, an overview of EV charging methods and the standards applied to conductive charging systems are explained. Then, the smart charging ecosystem and the status quo on communication protocols that link the entities of this system to secure the charging infrastructures are given.

Several charging solutions exist for conductive charging (See Section 2.1). In this context, organizations such as IEC, SAE, IEEE, and CHAdeMO have established many standards for AC and DC charging modes. However, codes, standards, and protocols related to EV charging are often and sometimes incorrectly used interchangeably. Correct use of these terms should conform to their generic definitions:

Codes: Codes are recommended sets of rules that are not the law but can be adopted into law.

Standards: Standards are guidelines on meeting some codes used by product designers, manufacturers, installers, and operators. Policymakers select, adopt, and enforce codes and standards.

Protocols: A protocol defines the set of rules used by two or more parties to interact between themselves for communication and data exchange. Communication protocols can also be standardized.

It should be noted that codes, standards and protocols in the e-mobility field are prone to frequent modifications; therefore, the latest version of the standards mentioned here should be referred to before smart charging implementations.

2.1 EV Charging Infrastructures

Figure 2.1 summarizes EV charging techniques for BEVs and PHEVs, where battery exchange, conductive charging, and wireless charging are the three main charging techniques [18]. In this thesis, when EV charging methods are mentioned, conductive charging methods are actually meant.

On-board charging (OBC) solutions are supplied by the AC grid through an on-board battery charger device where energy conversion is carried out. As a result, the charging rate depends on the current capability of the AC plug, cable, and the ratings of the on-board battery charger device. On the other hand, in DC charging solutions, the charging stations are supplied by the AC grid as well. However, the charging rate is significantly higher since there are almost no limitations in size and weight compared to OBC, thanks to the off-board nature of the installation. These chargers are used in DC fast charging stations (FCS).

Due to the contrast in their charging rate capabilities, waiting times to get the vehicle fully charged differ considerably between on-board and off-board chargers. Thus, charging power levels are generally classified into two groups: slow and fast charging [23]. Slow charging signifies the distributed charging with residential chargers

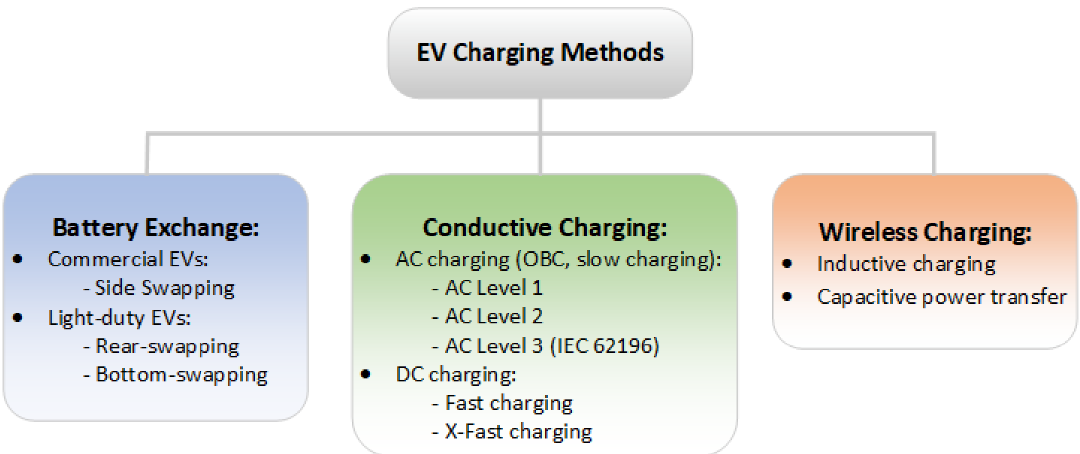


Figure 2.1: Types of EV charging solutions.

and AC public chargers with a power rate lower than maximum household power (e.g., 22 kW in Europe and 19.2 kW in the USA [26]).

2.1.1 International Standards Defining Charging Modes/Levels and EVSE

The charging modes/levels encountered in Europe and the USA are included in IEC 61851 (international standards for electric vehicle conductive charging systems) and IEC 62196 (international standards for charging couplers), and SAE J1772 (General, physical, electrical, communication, and performance requirements for conductive charging systems) [14]. These standards are maintained by the International Electrotechnical Commission (ICE) and the Society of Automotive Engineers (SAE) International and updated with the increasing charging powers as the EV charging technology progress.

IEC 61851 establishes the international standards for the general characteristics, charging modes, connection configurations, and requirements (including safety requirements) for specific implementations of EVs and EVSEs. IEC 61851 standards currently consist of 6 separate documents:

1. **Part 1:** General requirements,
2. **Part 21-1:** EV on-board charger electromagnetic compatibility (EMC) requirements for conductive connection to AC/DC supply,
3. **Part 21-2:** EV requirements for conductive connection to an AC/DC supply, EMC requirements for off board EV charging systems,
4. **Part 23:** DC EV charging station (DC EVSE),
5. **Part 24:** Digital communication between a DC EV charging station and an EV for control of DC charging,
6. **Part 25:** DC EVSE where protection relies on electrical separation.

Part 1 of the IEC 61851 Standards defines four modes of charging, which are summarized in Table 2.1.

Table 2.1: EV charging modes based on IEC 61851-1 (General requirements)

Mode	Voltage	Current	Notes
1	1ph,250V 3ph,480V	16A	**Standard socket outlet - domestic installation:** AC portable charger, no communication requirements. Direct connection of vehicle to conventional electrical outlets. Not safe.
2	1ph,250V 3ph,480V	32A	**Standard socket outlet with AC EVSE - domestic:** AC portable charger with communication and safety requirements. EVSE provides earth detection and monitoring; over-current and ground fault protection, heating protection; functional switching depending on vehicle presence and charging power demand. Requires control box between vehicle and electrical outlet. Not safe for public charging.
3	1ph,250V 3ph,480V	32A	**AC EVSE permanently connected to an AC supply network:** AC stationary charger with communication and safety requirements. The communication wire between EV electronics and EVSE allows for integration into smart grids. EVSE is permanently connected to grid. Typical public charger installation.
4	400V	200A	**DC EVSE:** Fast charging using charger technologies such as CHAdeMO. DC stationary charger with communication and safety requirements. Current conversion handled by EVSE, not EV.

SAE J1772, formally titled "*SAE Surface Vehicle Recommended Practice J1772, SAE Electric Vehicle Conductive Charge Coupler*", defines the North American standards for general, physical, electrical, communication, and performance requirements for EV conductive charge system and operational, functional, and dimensional requirements for the vehicle inlet and mating connector. Table 2.2 compares the standard charging levels based on the SAE J1772.

Among the charging levels in the table, DC levels are typically used for commercial FCSs and capable of providing a wide range of input and output voltages. AC Level 1 requires 120 V which is typical in residential and commercial buildings. However, the power rate of AC Level 1 is insufficient for fully charging EV batteries that are fully discharged or that have high capacity, making AC Level 1 charging only suitable

Table 2.2: EV charging levels based on SAE J1772 standards

Charging Level	**Input Voltage**	**Output Voltage**	**Maximum Current**	**Maximum Power**
AC 1	120V	120V	16A	1.9kW
AC 2	208-240V	208-240V	80A	19.2kW
DC 1	208-600V	50-1,000V	80A	80kW
DC 2	208-600V	50-1,000V	400A	400kW

for overnight charging in residential charging locations. AC Level 2 requires 240 V for residential buildings and 208 V for commercial buildings, which makes it suitable for smart charging strategies and non-smart charging strategies for non-domestic applications [27]. Although a third AC charging level for three phase charging was considered by the SAE, it was never implemented for light duty vehicles.

The motivation of SAE J1772 is to determine a common electric vehicle conductive charging system architecture in the USA by gathering the international standards for EVSE, EV, and communication between EV and EVSE under a single title. To this end, SAE J1772 references:

- IEC 61851,for the general requirements of charging EVs at standard AC supply voltages and DC voltages, including low-level EVSE-EV communication,
- IEC 62196, for the general requirements of AC and DC charging plugs, sockets, outlets, inlets, connectors, and cable assemblies for EVs,
- ISO/IEC 15118, for the general requirements on high level communications enabling smart charging.

2.1.2 International Standards on EV Coupler Configurations

IEC 62196, *Plugs, socket-outlets, vehicle connectors and vehicle inlets – Conductive charging of electric vehicles*, defines the international standards of electrical connector sets for AC and DC charging. IEC 62196 (Part 1: General requirements) provides a broad characterization of the interface between EV and EVSE, including the mechanical and electrical requirements and tests for charging equipment.

Specific designs for AC charging in the modes 1, 2, and 3 as defined by IEC 61851-1 are explained by IEC 62196-2 (Part 2: Dimensional compatibility and interchangeability requirements for AC pin and contact-tube accessories), which extends IEC 62196-1. The specific designs are grouped into three types: Type 1 (Figure 2.2a, 2.2b), Type 2 (Figure 2.2c, 2.2d), and Type 3 (deprecated). These configurations consist of vehicle couplers (vehicle connectors and vehicle inlets).

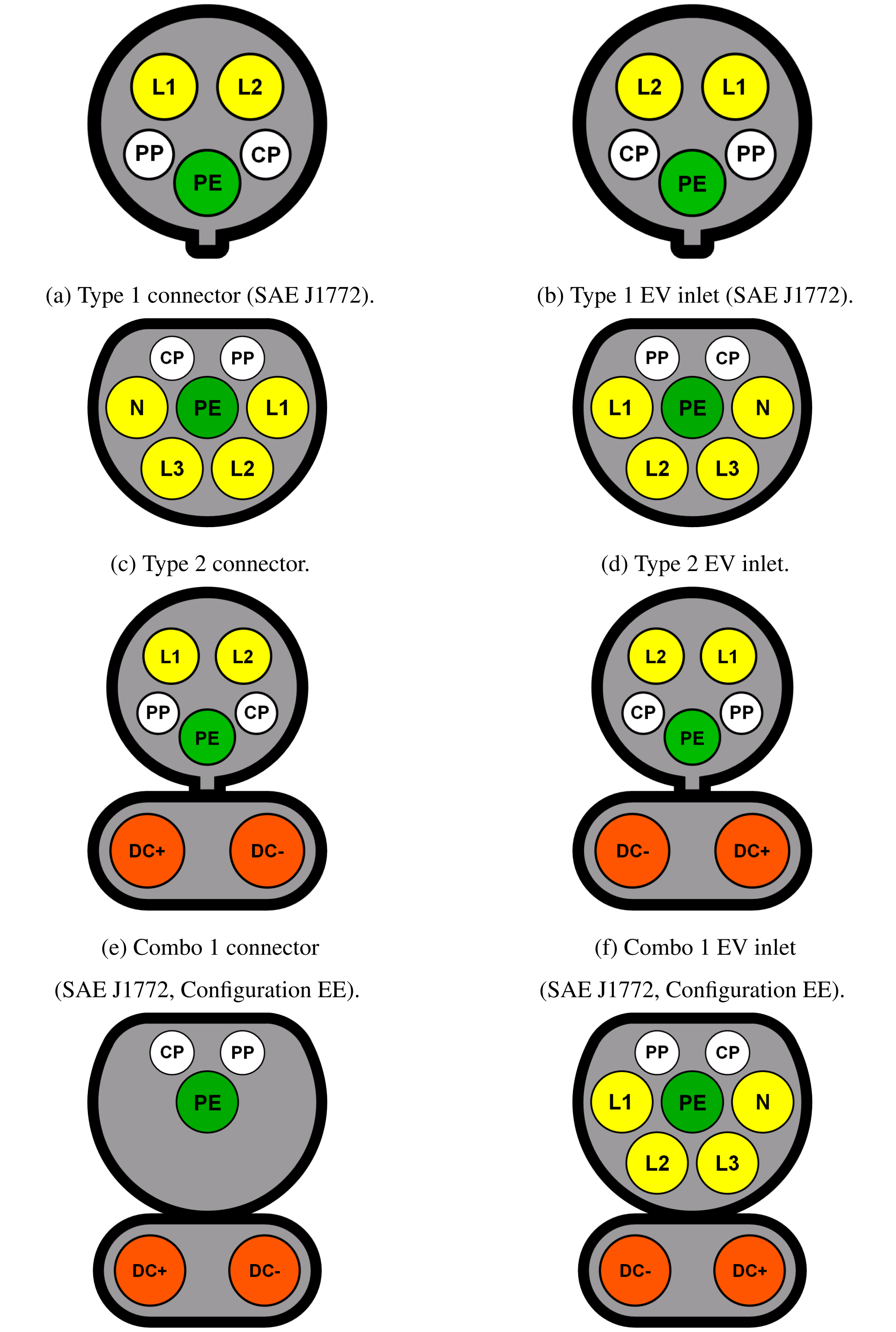
- Type 1 connectors (Figure 2.2a), colloquially known as the Yazaki connectors or SAE J1772 connectors, are predominantly used in the US. This type only supports single-phase charging with an operating current of up to 32 A. However, it allows a maximum current of 80 A in the USA, where SAE J1772 also describes this higher operating current.
- Type 2 connectors (Figure 2.2c), also known as the Mennekes connectors, are used in all public AC charging stations within the EU as required by regulation. This type supports three-phase charging allowing operating currents up to 63 A and a maximum current of 70 A for single-phase applications.

In addition to the AC conductors, these connectors have a protective conductor (Protective Earth) and two signal pins that are used for the control pilot and proximity plot utilized in signaling functions enabling the *EV and EVSE handshake protocol*, which is explained further in Section 2.2.1.1.

IEC 62196-3 (Part 3: Dimensional compatibility and interchangeability requirements for DC and AC/DC pin and contact-tube vehicle couplers) references IEC 62196-1 to describe specific configurations of EV couplers intended to be used for DC charging in Mode 4 as clarified by IEC 61851-1. The specific configurations, namely, *Configurations AA, BB, EE, and FF*, allow compatibility between products of different manufacturers:

- **Configuration AA:** Colloquially known as the CHAdeMO connector (Figure 2.3), intended to be used with DC charging stations that implement System A[1] and CAN-communication.

[1] Described by IEC 61851-23.



(a) Type 1 connector (SAE J1772).

(b) Type 1 EV inlet (SAE J1772).

(c) Type 2 connector.

(d) Type 2 EV inlet.

(e) Combo 1 connector (SAE J1772, Configuration EE).

(f) Combo 1 EV inlet (SAE J1772, Configuration EE).

(g) Combo 2 connector (Configuration FF).

(h) Combo 2 EV inlet (Configuration FF).

Figure 2.2: Predominant EV coupler configurations in the USA and EU[2].

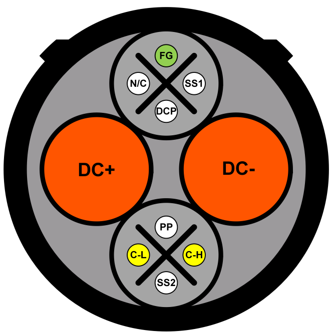
[2]Male and female pins are not specified in the images. Pin-outs are **L:** AC power, **N:** neutral, **PE:** Protective earth, **CP:** Control pilot, **PP:** Proximity plot, **DC+** and **DC+/DC-**: DC power

- **Configuration BB:** Intended to be used with DC charging stations that implement System B[1] and CAN-communication. It is mostly used in China with GB/T connectors (Figure 2.3b).

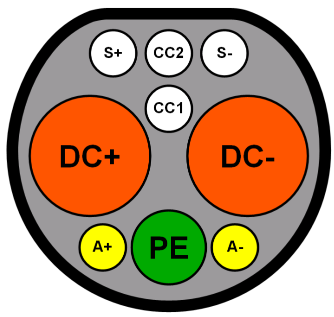
- **Configuration CC and DD:** Reserved for later use.

- **Configuration EE:** Extends the Type 1 coupler. Also known as Combined Charging System (CCS) 1 connector" or Combo 1 connector. This configuration is intended to be used with DC stations that implement System C[1] and PLC communication[3].

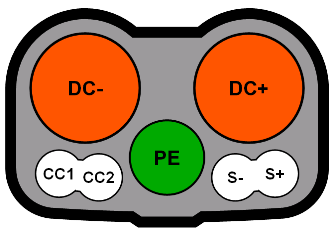
- **Configuration FF:** Extends the Type 2 coupler. Also known as CCS 2 connector" or Combo 2 connector and is intended to be used with DC stations that implement System C[1] and PLC communication[3]. It is used in all DC charging stations within the EU as required by regulation.



(a) CHAdeMO connector (Configuration AA).



(b) GB/T connector (Configuration BB).



(c) ChaoJi connector

Figure 2.3: Predominant DC couplers in China and Japan [4].

[3] According to IEC 61851-24 and ISO 15118-3.

[4] Male and female pins are not specified in the images. Pin-outs are **FG**: Ground, **SS1 / SS2:** Charge sequence signal, **N/C:** not connected, **DCP:** Charging enable, **DC+/DC-**: DC power, **PP:** Proximity plot, **C-H/C-L:** CAN bus, **PE:** Protective earth, **CC1/2:** Connection confirmation, **S+/-:** CAN bus.

2.2 Communication Protocols Linking Smart Charging System Entities

This section presents the status quo on communication protocols and standards for the integration of EVs into the smart charging infrastructures. For proper adoption of EVs into the electricity grid, informational and control objects are exchanged across the ecosystem entities. Data such as EV identification, SoC, battery size, and charging demand would flow up from EV to third-party entities. Based on the EV requests and the system state (e.g., frequency, current, voltage, and pricing data), EVSE set points are determined and sent down to control the charging process [20].

Communication standards linking the system entities focus on two key considerations pertaining to EV charging: charging interoperability [28] and the cybersecurity of smart charging systems [29]. *Interoperability* refers to the ability of a range of EVs, EVSEs, and charging networks to interact with each other through all levels of charging control [30]:

- **EV to EVSE communication:** EVs should be able to interact with different chargers, which requires the compatibility of plugs and connectors. These communication protocols include the front-end protocols communicating a safe connection 'handshake' between EV and EVSE, ISO 15118 (International standards of vehicle to grid communication interface).

- **EVSE to charging network communication:** These back-end protocols enables different EVSE models to interact with each other and with other charging management systems so that the third party operators better manage EVSEs and services like station locator websites or mobile applications are enabled.

- **Charging network to charging network communication:** These protocols allow CPOs and other third party operators to communicate with each other so that services like network roaming (members of one network charging on another network) and aggregator functions are possible.

2.2.1 Front-end protocols

Front-end protocols includes the communication protocols between the EV and the EVSE. EV chargers are equipped with different communication and control capabilities to foster smart charging, as expressed in Table 2.3 [11].

Table 2.3: EV supply equipment communication and control levels

Levels	Communication and Control Capabilities
1	EVSE charges EV directly when it is plugged in. Only primitive communications for safety precautions such as Proximity detection, Ground fault indicator, EV and EVSE "handshake" are available.
2	All the features of Level 1. Additionally, charging time can be delayed by EV owners by controlling the start/end times of charging.
3	All the features of Level 2. Additionally, EVSE has two-way communications with the electric utility. EVSE can receive an on/off enabling signal from the electric utility, charging rate of the EVSE can be adjusted. Reports vehicle identification to the electric utility when the vehicle is plugged in if Plug&Charge is enabled.
4	All the features of Level 3. Additionally, bidirectional power flow (V2G) is enabled.

2.2.1.1 SAE J1772 Signaling Protocol

This signaling protocol enables the *EV and EVSE handshake*, and is defined by SAE J1772 the signal pins and their functions in Type 1 connectors, and subsequently included in IEC 61851. In addition to the AC and DC conductors, EV connector configurations in Europe and the USA have a protective conductor and two signal pins that are used for the *control pilot (CP)* and *proximity plot (PP)* functions (Figure 2.2).

PP function allows the EV to detect when it is plugged in and prevent movement while connected to EVSE.It is also used to indicate the maximum current capability of the cable assembly to the EVSE. The EVSE interrupts the supply current if the current capability of the cable is exceeded. CP is a communication line allowing the EVSE to detect the presence of the EV, communicate the maximum allowable charging current with pulse width modulation (PWM), and control charging begin/end. This pilot signal sets an upper limit on the rate at which the vehicle will charge. The vehicle can charge at any rate up to this limit.

The signaling protocol is designed so that the EVSE awaits powering the charge plug until plugged into and commanded by the EV [31]:

1. The EVSE signals the presence of AC input power.
2. The EV detects the charging plug via a proximity circuit (thus, the EV can prevent driving away while connected) and detect when the latch (a type of mechanical fastener) is pressed in anticipation of plug removal.
3. Control Pilot (CP) functions begin:
   - The EVSE detects the EV,
   - The EVSE indicates the EV its readiness to supply energy,
   - EV ventilation requirements are determined,
   - The EVSE's current capacity is provided to the EV.
4. The EV commands the energy flow.
5. The EV and EVSE continuously monitor the continuity of safety ground.
6. Charging continues as determined by the EV.
7. Charging may be interrupted by disconnecting the plug from the vehicle.

The EV and EVSE handshake communicates a safe connection 'handshake' between EV and EVSE and fosters only Level 1 communication and control capabilities by itself. Level 2 capabilities are achieved when the CP is manipulated by the EV's side to initiate charging. Level 3 smart charging capabilities are accomplished by controlling the plot signal by incorporating additional modules to the charger with the following steps [32]:

1. The CP's PWM signal is measured to determine the maximum power EVSE can deliver in uncontrolled charging.
2. An identical CP signal is created to command the EV to reduce its maximum charging power.

3. The battery management system of the EV adjusts its charging rate in response to the manipulated CP signal.

It should be noted that the actual charging rate of the EV might be below the CP signal. Since this signaling protocol defined by SAE J1772 does not provide a mechanism for getting information such as state-of-charge (SoC) from the EV, it can be difficult to diagnose why the EV is charging below its allocated pilot signal. Secondly, most commercially available EVSEs only support a discrete set of pilot signals, and EVSEs impose limits on the pilot signals they support. The SAE J1772 handshake protocol does not allow pilot signals below 6 A but 0 A, i.e., not charging [33].

2.2.1.2 IEC-ISO 15118: Vehicle to Grid Communication Interface

ISO 15118 defines the international standards on V2G communication interface for bi-directional charging and discharging of EVs. It allows wireless charging and conductive AC and DC charging as a part of the CCSs. ISO 15118 deploys the *Plug & Charge* feature, which unlocks the following:

- With the utilization of Public Key Infrastructures (PKIs) and Certificate Authorizations (CAs), automated authentication, authorisation and billing of the charging event can start as soon as the driver connect the EV to the EVSE without the need for additional authentication methods, such as smart phone apps, RFID cards.

- An enhanced data security features comes with the cryptographic mechanisms defined by the standard.

- EV and charging station can exchange messages using either a charging cable[5] or a Wi-Fi connection[6] as a physical medium.

[5] Power Line Communication via a Home Plug Green PHY modem as described in ISO 15118-3
[6] IEEE 802.11n as referenced by ISO 15118-8

2.2.2 Back-end Protocols

Back-end protocols include the communication protocols between the charger and the third-party operators in the smart charging ecosystem. The back-end communication protocols enabling charging interoperability are as follows:

Open Charge Point Interface (OCPI): The EVRoaming Foundation manages OCPI. It links two charge point operators together through a service provider that provides *roaming* so that EV owners can use Company A's app to pay for charging done on Company B's charging station [30]. The protocol facilitates automated roaming for EV owners across several EV charging networks and promotes EV adoption by making the following benefits available:

- Underpinning the affordability and accessibility of charging infrastructures for EV drivers by allowing drivers to charge on several networks. (Conventionally, EV owners had to be members of each company to use their services and download different apps to connect the charging stations.)
- Reducing charging anxiety by providing accurate data such as location, accessibility, and pricing.
- Enabling real-time billing and mobile access to charging stations.

Open Charge Point Protocol (OCPP): OCPP is a communication protocol between charging points or EVSEs and charge point operators. This protocol handles the exchange of charging data and trade information between EVs and the TSO/DSO. The protocol is maintained by the Open Charge Alliance (OCA). OCPP has the following additional functionalities [30]:

- Separates the physical aspects of the EVSE from the network back-end entities,
- Allows site host to switch networks without replacing entire EVSEs.

Open Automated Demand Response (OpenADR): OpenADR is an open secure-two-way information exchange model for DERs, facilitating automated demand response (DR) actions for grid balance and cost minimization. It DR actions by relying on a gateway device, or aggregator to translate DR orders of the utility and DER requirements into specific device behaviours. The OpenADR protocol ensures the dynamic balance and reliability signals are exchanged between the third-party operators in the smart charging ecosystem during DR operations. The OpenADR Alliance fosters this communication protocol.

IEEE 2030.5: This standard is a group of communication protocols to connect and directly control home area network devices and references to IEC 61850 (International standards on communication protocols for intelligent electronic devices at electrical substations). It is not directly related to EV mobility since it applies to home EV chargers. However, it allows communication between the relevant entities for smart charging, such as aggregators, home-smart devices, EVSE, and the EV.

IEC 63110: IEC 63110 provides the international standards on the management of EV charging/discharging infrastructure. It has both front-end and back-end communication functions since it enables interoperability in the front-end communication between EV and EVSE and enables smart grid integration allowing all the actors in a specific market to interact together. IEC 63110 also facilitates bi-directional charging. It is currently under development and expected to have the following parts in separate documents:

Part 1: Basic definitions, use cases and architectures

Part 2: Technical protocol specifications and requirements

Part 3 Requirements for conformance tests

IEC 63119: IEC 63119 sets the international standards on information exchange for electric vehicle charging roaming service. It specifies the terms and definitions, general description of the roaming system model, classification, information exchange and security mechanisms for roaming between e-mobility service providers, CPOs and some other third-party operators for roaming purposes.

Interfaces linking EV with EVSE, CPO, and other third-party operators, interfaces linking EVSE with smart energy management systems (EMS), CPO, and other third-party operators, and interfaces between CPOs and other third-party operators are illustrated in Figure 2.4. The figure also shows where the front-end and back-end protocols apply to the interfaces between smart charging ecosystem entities.

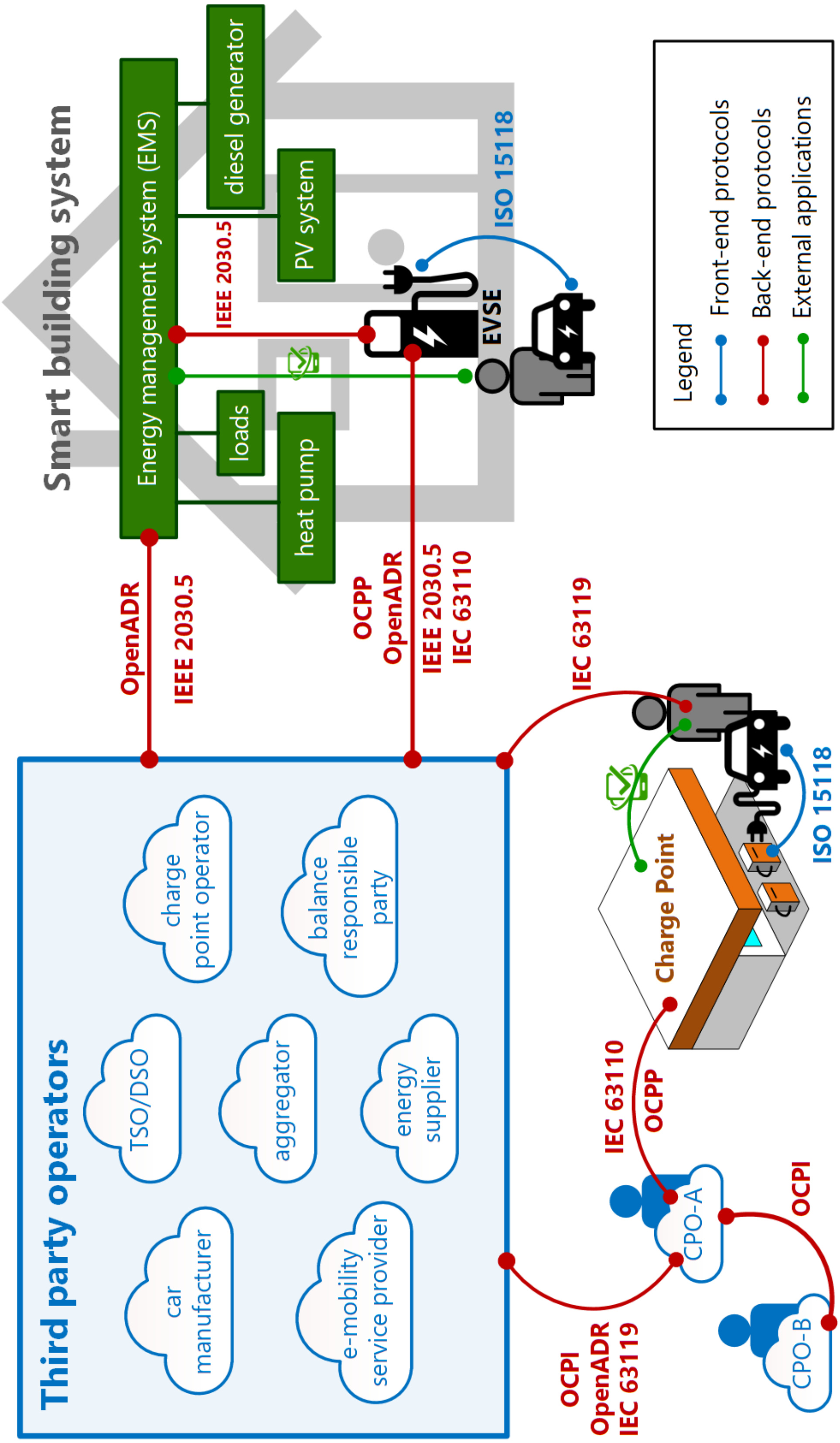


Figure 2.4: Communication protocols linking smart charging ecosystem entities.

2.3 Conclusion

This chapter explained the standards on conductive charging systems such as EV charging modes/levels and applied standards to EVSE and EV couplers. Moreover, the interfaces between smart charging ecosystem entities and communication protocols enabling smart charging were provided. Not all charging standards comply with the communication protocols enabling smart charging. Smart chargers facilitate the necessary hardware and software for exchanging information and control signals between EV-EVSE and EVSE-operator to manage the time and speed of charging (i.e., power rate). To unlock these features, additional hardware and software must be included in non-smart chargers.

Security of the smart charging entities against cybersecurity attacks is out of the scope of this chapter. However, among the front-end and back-end communications explained in this chapter, a combination of Open Charge Point Protocol 2.0 (OCPP 2.0) and ISO 15118 with Transport Layer Security (TLS) protocol would prevent cybersecurity attacks against the charging system [20]. This combination would secure the communication interfaces between EV-EVSE, EV-central management system, and EVSE-central management system. More information on this topic can be found in [20], [29], and [34].

CHAPTER 3

ELECTRIC VEHICLE LOAD MODELING FOR CHARGING OPTIMIZATION

This chapter presents a method to develop the individual load models of EV users while keeping the identity of the drivers for coordinated charging strategies and provides a coordinated charging algorithm for workplace chargers. The structure of the chapter is as follows:

Section 3.1 gives an overview of the EV load modeling and the related literature on EV load modeling techniques. In Section 3.2, a method based on Kernel Density Estimation is proposed to model individual EV loads. First, commonly used density estimation approaches in machine learning are discussed to select the best representation of charging patterns. Next, the characteristics of the utilized dataset and the proposed method based on KDE are explained. Also, the necessity of separately modeling the EV drivers is shown by investigating the cumulative density functions of the random variables describing individual EV loads. In Section 3.3, a coordinated charging control algorithm for workplace chargers with a single system-time horizon is devised to demonstrate how the individual load models can be utilized in the charging optimization process. A simulations subsection that compares uncoordinated, coordinated, and First Come First Serve charging approaches is presented. The results show that individual load models complement smart charging algorithms' decision processes by ensuring each EV is charged at least a critical amount given a feasible set of optimization constraints. The chapter concludes with a conclusion section on the findings.

3.1 Electric Vehicle Load Models

Integration of EVs in power system operation is one of the primary subjects in demand side management. Thus, multiple research studies have addressed uncontrolled EV charging problems by proposing various EV charging control methods to minimize the peak-valley load difference, infrastructure costs, and losses [27]. In addition, EVs can be used to improve the efficiency and reliability of the power grid with the vehicle to grid (V2G) option [17]. Therefore, it is of great interests for system operators and aggregators to extract EV charging profiles from accumulated charging demands, smart meters with non-intrusive load monitoring (NILM), or using individual driving profiles so that;

- Unrealistic and uncertain assumptions on demand profiles can be alleviated;
- EV charging profiles can be accurately extracted to support system operations and planning [35, 36].

Due to spatial-temporal random dynamics of EVs, particularly passenger light-duty ones, identifying and positioning the space and time-varying impacts on drivers' charging behaviors are challenging. Reference [37] provides a comprehensive review of published data sources for EV studies focusing on deriving charging profiles to analyze and mitigate the EVs' impact on the power system. The data sources have evolved from surveys and internal combustion engine vehicle to EVs and charger trials over the last two decades. While the former works on charging demand models rely on passive observations of driving patterns and charging profiles aiming to analyze the impact of EV loads on the grid [38, 39, 40], recent works take charging sessions as their primary data source [22, 41].

In [38], statistical charging load modeling of plug-in electric vehicles in electricity distribution networks is studied using National Household Travel Survey dataset, which contains the home arrival/departure times of 1 million vehicles. In [39], the data including the driving mileage and parking behavior of 1463 EVs in China were collected for a year. My Electric Avenue project in the UK deployed over 200 Nissan LEAFs to observe the driving and charging habits of a geographically and socioeconomically diverse population for two years [40]. A dynamic dataset of workplace EV charging with over 30,000 charging sessions is provided by Adaptive Charging Network Data in [22]. A real-world pilot study in [41] investigates the latent flexibility of EV charging utilizing residential charging sessions recorded over New York.

The overwhelming majority of the studies in the literature propose methods to model the accumulation of a group of EVs' charging demands [27]. Reference [42] proposes the use of probability density functions (PDFs) based on normalized histograms and Gaussian Mixture Models to represent key charging metrics of EVs. EV load demand is represented using fuzzy logic membership functions in [43]. The authors of [44] proposes an Agent Based Model by examining factors influencing charging behaviors to predict the charging demand of different types of EVs under various circumstances in order to optimize the locations of charging stations. The use of the Monte Carlo simulations for temporal and spatial transportation behaviors is suggested in [45]. Discrete-time Markov chains are utilized to model the stochastic nature of EV charging by the authors of [46]. On the other hand, [47] and [35] adopt NILM to extract charging profiles from individual metering appliances.

These EV load modeling studies concentrate on analyzing the impact of charging profiles on the power system to optimize the system design. Online EV charging scheduling strategies can benefit from these models for extracting the expected values of future arrival rate and charging load demand of EVs; however, individual vehicle owners' perspectives are overlooked since accumulated loads are used.

EV load modeling researches have concentrated on the aggregator's and system operator's perspectives. Hence, the literature focuses on the modeling of EV loads grouped together. On the other hand, simple empirical predictions or direct user input are commonly used in practical control of EV charging scheduling systems. Individual load profiles are not favored in the literature for the reasons listed below:

- For residential applications, it is costly to install additional sampling devices into existing residential EV chargers, and unrealistic to sample and communicate EV charging information to system operators [35].
- GPS measurement data-sets for individual driving profiles are scarce with most

of them covering over a restricted period, area, and drivers.

- The number of decision variables inherent to individual driving patterns is exorbitant [36].
- Charging scheduling algorithms in commercial charging stations rely on direct user input.

However, identity retained individual charging profiles can be convenient in some applications. For example, this kind of EV load modeling can benefit corporations that pay car allowance to employees. Corporations usually keep the arrival/departure times of the employees to track working hours, leaving only the daily charging duration data to be stored additionally.

Commercial charging stations rely on causal information such as connection duration and energy demand defined by customers at arrival to the station. Classic online EV charging scheduling algorithms optimize the load demand revealed at the current time but underestimate the load demand revealed in the future [48]. On the other hand, individual EV load modeling provides partial knowledge of future charging demand data. Moreover, user input data can be quite unreliable for practical EV charging systems, as proven in [21].

3.2 EV Load Modeling with Kernel Density Estimation

3.2.1 Density Estimation Methods

The most popular density estimation techniques are statistical models such as normalized histogram, mixture models such GMM, and neighbor-based approaches such as KDE. Among these methods, histogram as a density estimator is an inferior option compared to GMM and KDE as it can lead to representations that have qualitatively different features based on the choice of bin size and locations [49].

The GMM is a parametric density estimator for D-dimensional data, which assumes all the data points are generated by a convex combination of a finite number of Gaussian distributions. However, it requires specifying the number of clusters and the locations, μ_k, of each cluster. KDE solves this issue in a non-parametric way by allocating one Parzen window per data point, so $\mu_i = x_i$ for each data point i.

The generalized KDE approach is given by (3.1). In (3.1),$\kappa_h(x)$ is Kernel function with bandwidth h and μ_k the location of cluster k. x_i represents the data-point i of a dataset that has N number of data point.

$$\hat{p}_X(x) = \frac{1}{N} \sum_{i=1}^{N} \kappa_h(x - x_i) \tag{3.1}$$

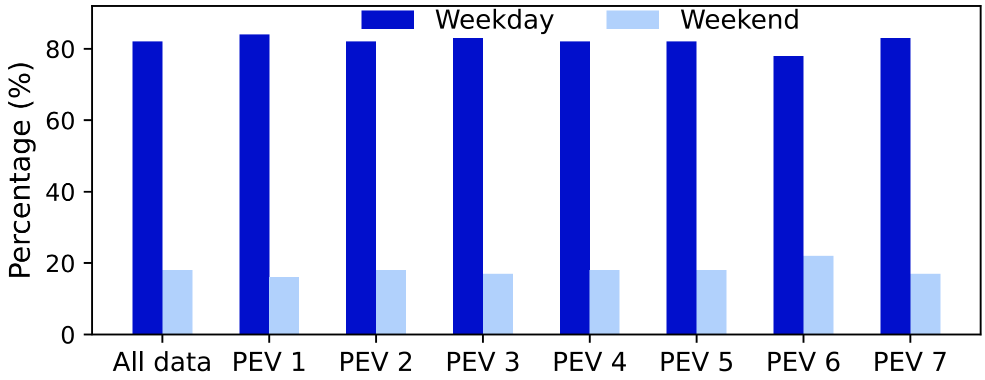
The advantage of KDE over a parametric GMM model is that except for tuning the bandwidth, no model fitting is required. The kernel function and bandwidth are the only things that need to be specified to estimate a density [50].

3.2.2 Personalized EV Load Models

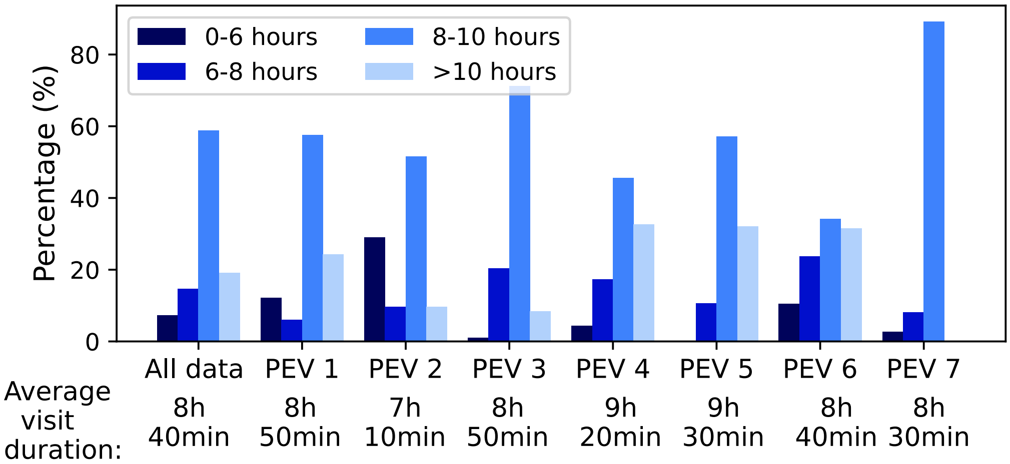
The EV's power demand from a charging station can be simulated using three random variables (RVs): arrival time at the charging area, time of departure from the charging area, and the charging amount. If these RVs have correlation, joint distributions must be utilized to explain the relationship among them. The following subsection studies the general characteristics of the arrival and departure times of the car owners in a given dataset. As a preventive solution, EV load models are utilized in smart charging system design and hardware selection.

3.2.2.1 Characteristics of the Dataset

In this work, we are making use of a dataset corresponding to the employees of a corporate tech firm. The dataset consists of the turnstile logs of a company recorded for three months with one-minute resolution. Figure 3.1 illustrates characteristics of each employee's visits to the workplace. The employees in this figure are EV owners. Hence, Employee *i* is referred as EV *i*, where *i* is the staff ID. Figure 3.1a displays percentages of weekday and weekend visits of each employee over their overall visits. Visits of the employees generally occur on weekdays; therefore, the effect of weekend visits is omitted in load modeling.



(a) Percentage of weekday and weekend visits over the total number of visits.



(b) Percentage of visit durations over the total number of visits.

Figure 3.1: Characteristics of each employee's visits to the workplace.

The employees are required to fill a working time quota resulting in similar visit duration means. The firm practices flexible hours, leading to different visit duration variances as illustrated in Figure 3.1b. This figure gives the visit duration distribution for each EV owner. The average overall visit duration is 8 hours and 40 minutes, while this value ranges between 7 to 9.5 hours when employees are considered separately. The diversity in duration distributions reveals that representing all drivers with a generalized RV is not feasible for a practical smart charging scenario. If the arrival and departure times were correlated, marginal PDFs of these RVs would state the duration time incompletely. A copula function would have to be used to create a joint distribution function to estimate RVs. There is no correlation between the arrival and departure times for the treated dataset due to the corporate's working policy; therefore, the marginal PDFs of the arrival and departure times can sufficiently describe the visiting behaviors of the drivers.

3.2.3 Density Estimation of EV load parameters

The conventional PDFs are limited to model the stochastic behavior of vehicle owners due to the complex characteristics of the EV load parameters. Density estimators can tackle this problem by estimating the PDF of an RV. A density estimator is an algorithm that produces an estimate of the D-dimensional PDF from a D-dimensional dataset.

The proposed method derives the PDFs with KDE to stochastically represent the arrival and departure times for each EV owner. For optimizing the bandwidth of the kernel functions, grid search with half minute resolution within an hour is carried out for each parameter and driver using Python *Scikit-learn* library [51]. In order to minimize the reduction in the training sets, leave-one-out cross-validation is used. For the selection of the kernel function, the cross-validation process is done once for each of the Gaussian and Epanechnikov kernel functions given by (3.2) and (3.3), respectively. The kernel that minimizes the estimation error is used to generate the PDFs of arrival and departure times.

$$\kappa_h(x,h) \propto \exp\left(\frac{-x^2}{2h^2}\right) \tag{3.2}$$

$$\kappa_h(x,h) \propto (1 - \frac{x^2}{h^2}) \tag{3.3}$$

Figure 3.2 illustrates the results of the procedure where the arrival and departure times of all drivers are used as the training set. In the figure, PDFs of the arrival and departure times are plotted on the associated normalized histograms.

The PDFs and cumulative density functions (CDFs) of each EV are graphed in Figure 3.3, which shows that CDFs of EV 3 and 7 start to increase and approach to 1 in a narrow time frame, whereas other owners have greater deviations. The variety in times of the day at which the CDFs reach the maximum value and their derivatives show that the drivers should be modeled separately since acknowledging the variance in the flexibility of each driver's connection time improves the fairness of charging time allocation.

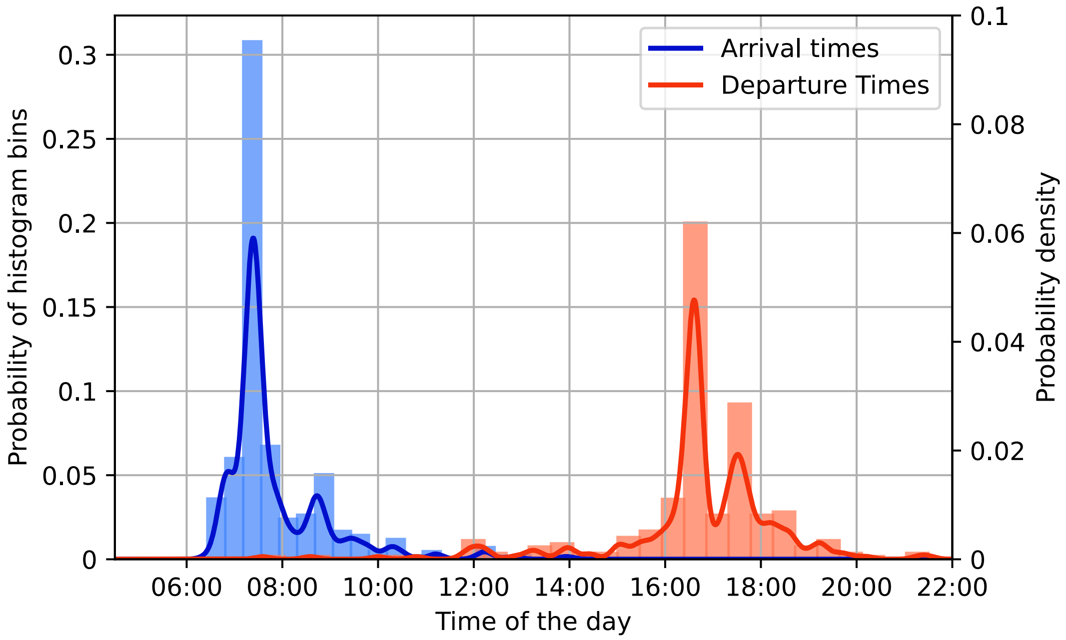
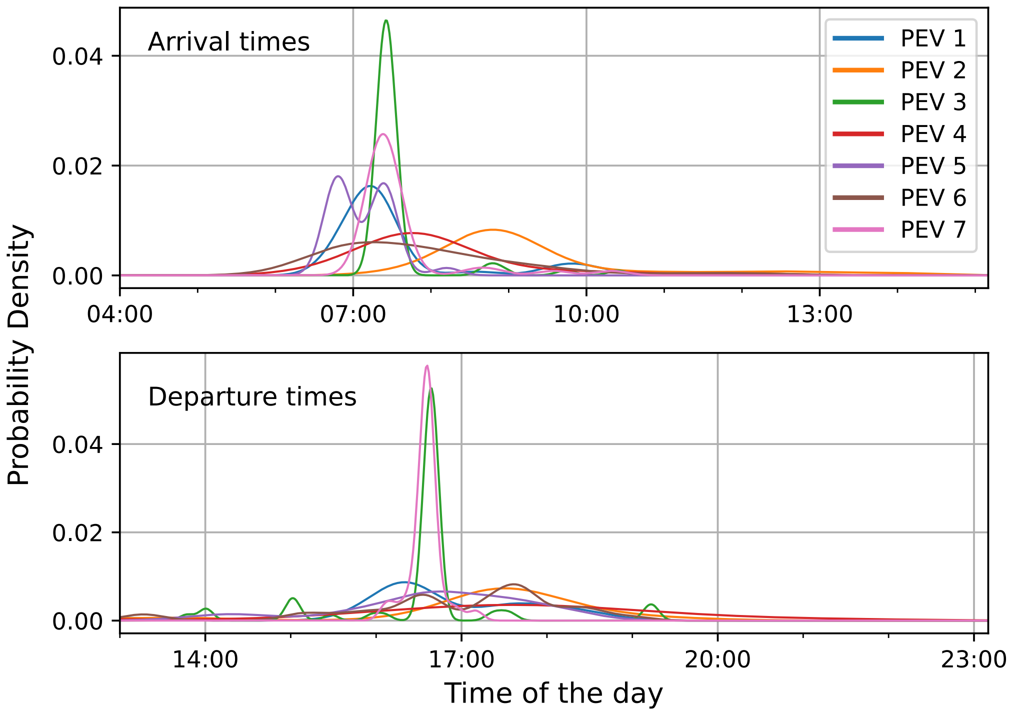


Figure 3.2: Distribution of arrival and departure times with associated PDFs.

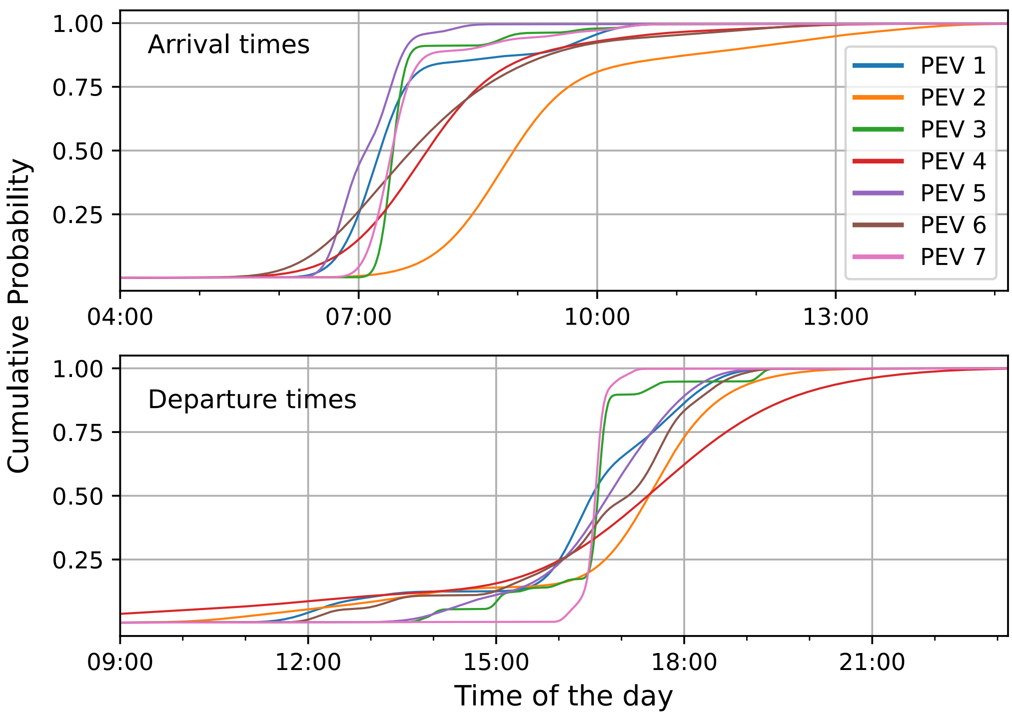
Energy requirements of EVs: While determining a smart charging strategy, identifying the energy requirements of the EVs is crucial. The KDE can be used to estimate the PDFs of charging amount, provided that the data of EVs' daily charging duration are retained. In this work, we assume that the energy requirement of each EV is estimated with proper accuracy. The energy requirement for a trip is strongly related to the route and the traffic congestion. The spatiotemporal analysis of recurrent congestions shows obvious and similar peaks in the morning and evening peak hours [52]. Thus, the mean of the energy requested from the charging network is utilized for a simple stochastic representation, assuming each driver follows the same route in their everyday commutes under similar traffic congestion levels.

3.3 Workplace Charging Utilizing Personalized Models

This section presents a coordinated charging algorithm that performs single deadline charging scheduling. The coordinated charging algorithm devised here decides whether a EV should be charged or not when the total charging demand is above the allowable demand.



(a) Probability density functions (PDFs).



(b) Cumulative density functions (CDFs).

Figure 3.3: PDFs and CDFs of the arrival and departure times of each EV.

Another solution to suppressing the charging demand could be using a First Come First Serve (FCFS) scheduling algorithm, which waits before charging another EV until the batteries of the currently charged ones are full. This process does not optimize the average waiting time, hence in most scenarios, the time a EV must spend in the queue would be longer than its duration in the charging network. Therefore, the necessary charging times and departure times must be compared before giving precedence to a EV, where individual EV load models come in useful.

3.3.1 Coordinated Charging Algorithm

The presented coordinated charging algorithm assigns a charging rate to each EV using based on a process of group assignments using stochastic energy consumption and departure times, which is summarized in Figure 3.4.

The algorithm uses four group of parameters in the decision process:

- **System inputs:** Allowable charging demand
- **EV inputs:** SoC_{now}, E_{bat}
- **User-defined inputs:** SoC_{des}
- **Stochastic inputs:** t_{crit}, SoC_{crit}

The stochastic inputs are calculated using the generated EV load models. SoC_{crit} is the minimum SoC necessary for the EVs when they leave the charging station considering the daily energy demand of the vehicle with a safety margin, in (3.4).

$$SoC_{crit} = min(100, SoC_{safety} + \frac{E_{stoc}}{E_{bat}}.100) \tag{3.4}$$

t_{crit} is the time of the day at which $F_{T_d}(t_d)$ reaches a predefined critical value. As the departure time must be greater than the actual time of the day, t_{crit} must be calculated

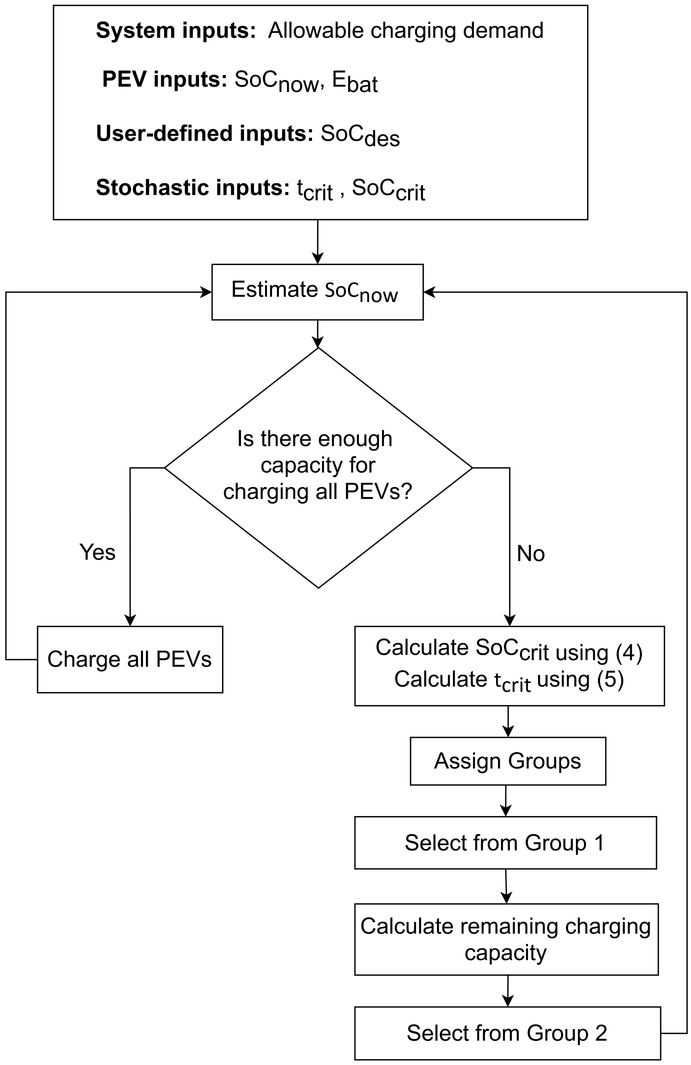


Figure 3.4: Flowchart of the coordinated charging algorithm

by the conditional CDF in (3.5).

$$\begin{aligned} F_{T_d|t_d \geq t_{now}}(t_d) &= \frac{P(T_d \leq t_d \mid t_{now} \leq T_d \leq t_d)}{P(t_d \geq t_{now})} \\ &= \frac{F_{T_d}(t_d) - F_{T_d}(t_{now})}{1 - F_{T_d}(t_{now})} \end{aligned} \tag{3.5}$$

If the allowable charging demand is less than actual demand, the algorithm assigns a group and subgroup to each EV according to Table 3.1.

Table 3.1: EV Groups Assigned by the Algorithm

<table>
<tr><th>Groups</th><th>Group condition</th><th>Sub-groups</th><th colspan="2">Sub-group condition</th></tr>
<tr><td rowspan="2">Gr. 1</td><td rowspan="2">$SoC < SoC_{crit}$</td><td>Gr. 1.1</td><td rowspan="2">Can SoC reach to SoC_{crit} before t_{crit}?</td><td>No</td></tr>
<tr><td>Gr. 1.2</td><td>Yes</td></tr>
<tr><td rowspan="2">Gr. 2</td><td rowspan="2">$SoC_{crit} < SoC < SoC_{des}$</td><td>Gr. 2.1</td><td rowspan="2">Can SoC reach to SoC_{des} before t_{crit}?</td><td>No</td></tr>
<tr><td>Gr. 2.2</td><td>Yes</td></tr>
<tr><td>Gr. 3</td><td>$SoC > SoC_{des}$</td><td colspan="3">No sub-groups</td></tr>
</table>

Group 1 is the EVs whose SoC are below SoC_{crit}, whereas Group 2 is the EVs whose SoC are between SoC_{crit} and SoC_{des}. Group 1 is with the priority and dispatched with a nonzero charging rate first, followed by Group 2. The subgroups indicate whether the EV loads have a higher probability of leaving the station earlier. Given equal energy demands EVs belong to the first subgroup must prioritize those in the second.

In order to optimize the average waiting time in the queue, each EV is assigned a value ϵ [0,v_g] by the value functions in (3.6) and (3.7) for Group 1 and 2, respectively, where v_g is larger for the first subgroup. Since $tanh(.)$ is a monotonically increasing function for the values in its non-negative domain, f_v increases with SoC_{now} within the same subgroup. The EVs with the highest values are charged first in order to select the EVs that can be transferred faster to a less prioritized group. This process aims to maximize the number of satisfied customers.

$$f_v = v_g.(1 - \tanh(k.E_{bat}.(SoC_{crit} - SoC_{now}))) \tag{3.6}$$

$$f_v = v_g.(1 - \tanh(k.E_{bat}.(SoC_{des} - SoC_{now}))) \tag{3.7}$$

After the selection of EVS in Group 1 using the values assigned to the EVs, the remaining charging capacity is dispatched among the EVs in Group 2 with the same approach. The dispatch is renewed after one minute with the updated parameters. Those EVs whose SoC reach SoC_{des} assigned in Group 3 are done with charging.

This decision process of the coordinated charging algorithm is explained in Algorithm 1.

Algorithm 1: Coordinated charging algorithm

System inputs : P_{max}

EV inputs : SoC_{now}, E_{bat}

User-defined inputs : SoC_{des}

Stochastic inputs : t_{crit}, SoC_{crit}

$\mathcal{N} \leftarrow$ The set of connected EVs that are not in Gr. 3

while $|\mathcal{N}| \neq$ **do**

  if *total demand* $\leq P_{max}$ **then**

    Charge all EVs

  else

    for $EV \in \mathcal{N}$ **do**

      Estimate SoC_{now}

      Calculate SoC_{crit} using (5)

      Calculate t_{crit} using (6)

      Assign group

      Calculate value using (7) and (8)

    end

    Sort $EVs \in \mathcal{G}_1$ based on value

    Select $EVs \in \mathcal{G}_1$ with highest values

    Calculate remaining charging capacity, P_r

    if $P_r > 0$ **then**

      Sort $EVs \in \mathcal{G}_2$ based on value

      Select $EVs \in \mathcal{G}_2$ with highest values

    end

  end

end

3.3.2 Simulations

The first test scenario concerns the morning peak in charging demands due to the majority of EV arrivals at the charging station occurring between 07:00 and 08:00, unveiled by Figure 3.3.

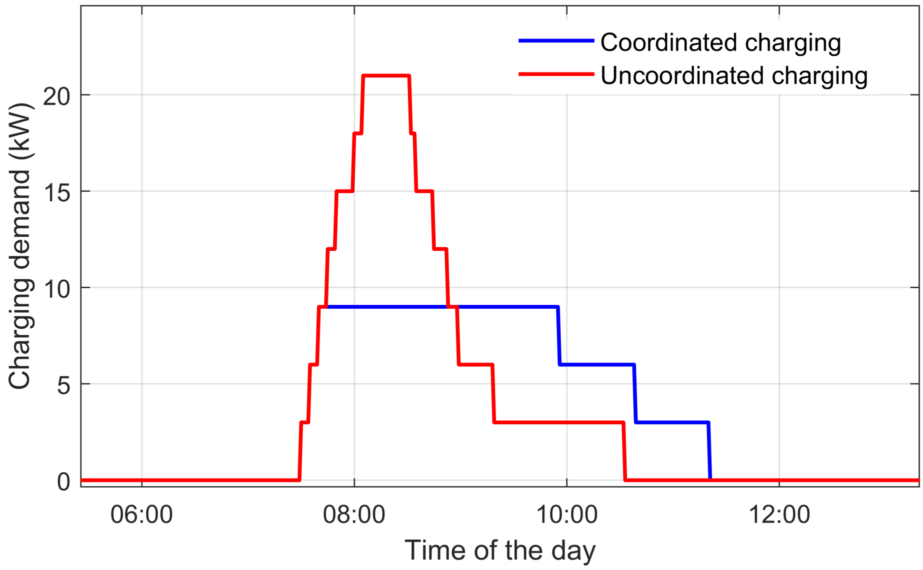


Figure 3.5: Total charging demand of the coordinated and uncoordinated charging.

In this scenario, all EVs arrive at the charging station within an hour, and the coordinated charging algorithm is used to stretch the morning peak over a more extended period. Figure 3.5 shows the total demand with the coordinated charging algorithm and the total demand if uncoordinated charging was implemented. Figure 3.6 presents the groups and subgroups assigned to each EV by the coordinated charging algorithm through the day with line graphs. Figure 3.7 demonstrates that the coordinated algorithm ensures all EVs reach their SoC_{crit} before attempting to charge any one of them fully through group assignments.

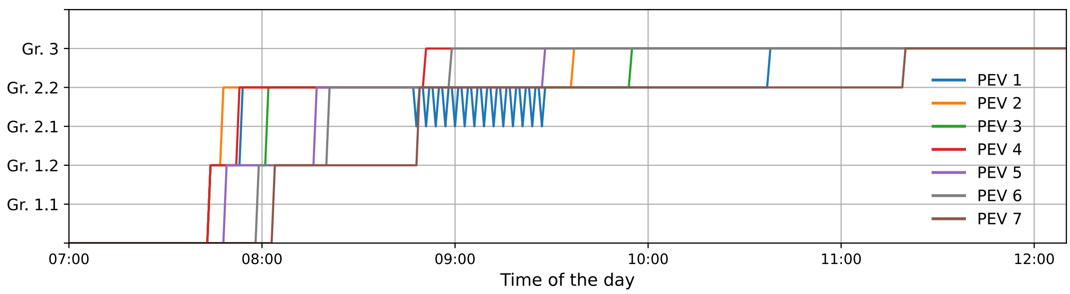
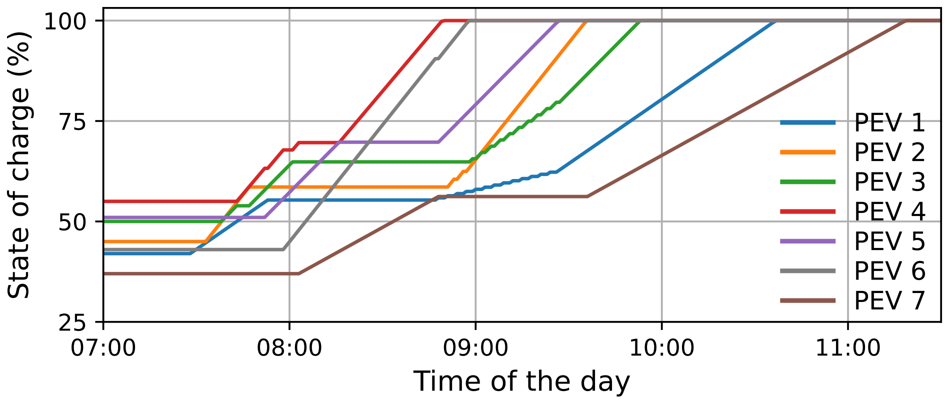
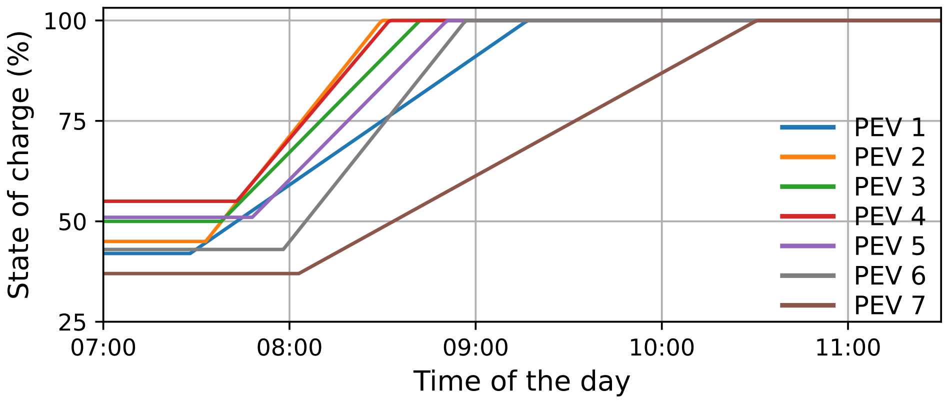


Figure 3.6: Groups assigned to each EV by the coordinated charging algorithm in Scenario 1.



(a) SoCs in coordinated charging of EVs.

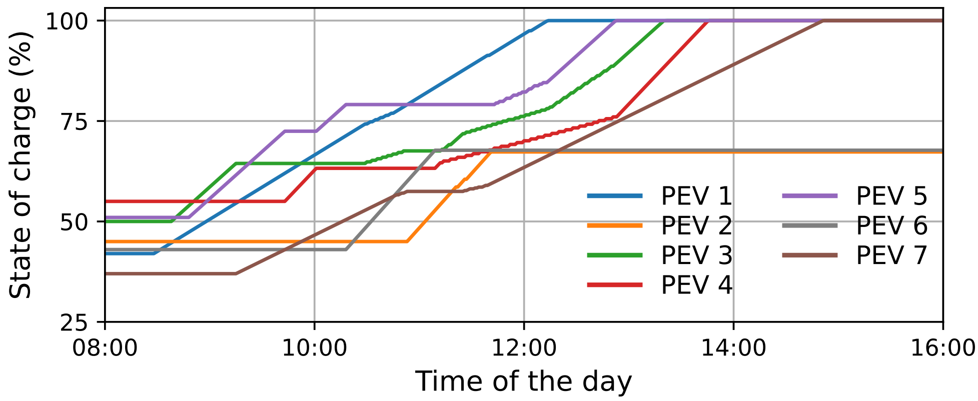


(b) SoCs in uncoordinated charging of EVs.

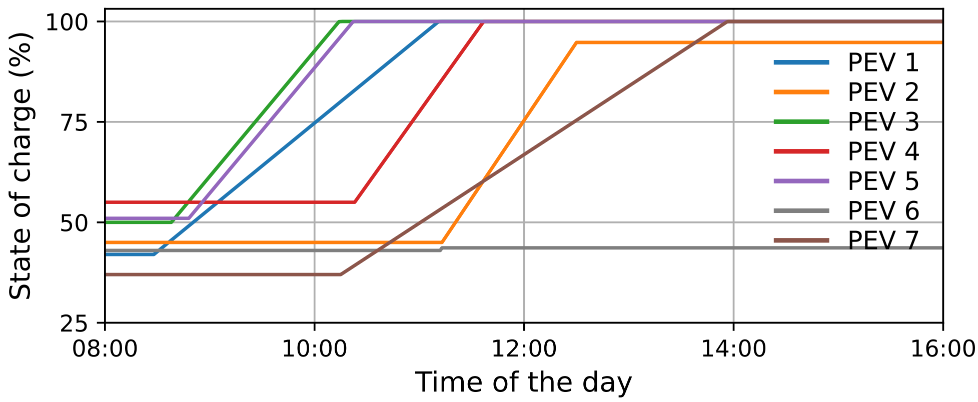
Figure 3.7: Comparison between SoCs in coordinated and uncontrolled charging methods in Scenario 1.

The second scenario studies the advantage of coordinated charging over FCFS strategy. In the second simulation, the EVs arrive at the charging station in a broader time frame. However, EV 2 and 6 arrive later than the other vehicles and leave before enough time for their batteries can be fully charged. Figure 3.8 illustrates the SoC of the EVs charged with FCFS scheduling algorithm and coordinated charging algorithm.

In Figure 3.8b, EV 6 leaves the grid with its arrival SoC since the FCFS algorithm does not start operating on it until shortly before its departure. In Figure 3.8a, the coordinated charging algorithm dispatches a nonzero CL to EV 6 at the expense of charging EV 2 shorter. Thus, both EV 2 and 6 are able to achieve their SoC_{crit}



(a) SoCs in coordinated charging of EVs.



(b) SoCs in FCFS control of EVs.

Figure 3.8: Comparison between SoCs in coordinated and FCFS charging methods in Scenario 2.

3.4 Conclusion

This chapter proposes the use of probability density functions based on Kernel Density Estimation to stochastically represent the arrival and departure time of individual EV loads to a charging station for real-time charging applications. A coordinated charging algorithm is presented to demonstrate how the individual load models complement the decision process of smart charging algorithms in the circumstances the maximum number of EVs charged simultaneously is constrained to shave the peak EV demand. Finally, the simulations compare the coordinated charging algorithm with uncoordinated charging and the First Come First Serve scheduling algorithm.

Smart charging applications have to consider the scalability of their algorithm and the speed of decision-making in large systems.

The coordinated charging algorithm assumes the availability of the SoC data from the vehicles. Although there are communication protocols enabling the SoC data exchange from the EV to the EVSE, the algorithm can easily be revised by incorporating smart meters keeping the total energy delivered to each vehicle.

CHAPTER 4

ELECTRIC VEHICLE CHARGING SCHEDULING

Charging scheduling algorithms select a subset of EVs from the set of EVs connected to a charging station and allocate their charging times and rates according to predefined optimization goals, system constraints, and charging demand of the EV owners. For example, charging an EV can be delayed according to VRE availability for cost minimization, or EVs can be charged with lower currents than the EVSE's capacity during peak demand hours not to violate transformer limits.

This chapter studies EV charging problems as a real-time resource allocation problem, i.e., scheduling problem where each EV charging task is identified by its arrival time, deadline, and processing time. The chapter is organized as follows:

In Section 4.1, an overview of the online EV charging scheduling problem is given. First, why the underlying optimization problem in charging scheduling algorithms is NP-hard and the feasibility of the charging constraints are explained. Then, the related work on charging scheduling algorithms in the literature is provided.

In Section 4.2, the single system-time horizon coordinated charging control algorithm in Chapter 3 is extended to a multi-objective scheduling algorithm considering a finite system-time horizon. First, the system description is given, followed by the explanation of the online charging scheduling algorithm. Finally, offline and online solutions to the scheduling algorithm are compared. The chapter concludes with a discussion in the conclusion section.

4.1 Charging Scheduling Problem

The charging scheduling problem deals with selecting and scheduling a subset of EVs in the set of $\mathcal{N} := \{1, 2, \dots, N\}$ over the decision-time horizon, $\mathcal{T} := \{1, 2, \dots, T\}$ given the charging demand of each customer, (a_i, d_i, e_i), and the peak constraints of the charging station, $\mathcal{P} := \{P^1_{max}, P^2_{max}, \dots, P^T_{max}\}$, and an objective function.

Charging scheduling problem requires the EVs connected to the station to be parked for an extended period provide the necessary flexibility for smart charging. Since the charging process is expected to be over in minutes in DC charging, the charging scheduling problem only applies to AC charging stations. Moreover, the rated power of EVSEs in the station should be high enough to satisfy the energy requirements of the EV owners and leave a flexibility margin for charging time allocation.

At a given time, $t \in \mathcal{T}$, the charging control algorithm can only know the causal information, i.e., the past and current information, or the charging profiles of the EVs that have already arrived if the user-input data are used [48]. If the complete knowledge of the future data is known before the beginning of system time, $t = 0$, the problem transforms into a deterministic case, which is called an *offline scheduling problem*. The algorithm adopted to solve the offline problem is called the *offline charging scheduling algorithm*. In practice, the optimal offline solution is not achievable for real-time charging scenarios due to the incomplete future information. Although offline charging scheduling algorithms make the unrealistic assumption of complete future information, they are used as a benchmark for evaluating the performance of *online scheduling algorithms*.

The underlying optimization problem of online charging scheduling algorithms possesses three key challenges:

1. Selection of the objective function
2. Computational complexity of scheduling problems
3. Inexistence of feasible solutions due to the constraints in some cases

Online charging scheduling studies focus on devising algorithms to tackle a selected subset of these challenges. The objective of EV charging control shows diversity depending on the operator's standpoint. The objectives could be fulfilling the charging demands before specified deadlines, maximizing the profit or social welfare, load shaping/peak shaving, cost minimization utilizing renewables, voltage/frequency control. In all cases, the critical challenge is the randomness and uncertainty of future data, including EV charging demands, electricity and regulation service prices, renewable generation, and the allowable total charging limit [53]. The knowledge of future random data is somewhat different in different applications. For instance, the online charging scheduling algorithm devised in this chapter utilizes $(a_i, d_i, e_i)^{stoc}$ for $i \in \mathcal{N}$.

4.1.1 Computational Complexity of Charging Scheduling Algorithms

A computational problem in P is said to be solvable in polynomial-time if the number of steps required to solve the problem is $\mathcal{O}(n^k)$, where n is the input length and k. An NP-hard (Nondeterministic Polynomial-time - hard) problem requires at least many steps to solve the most complex problem in NP, which is a complexity class that classifies decision problems whose solution can be verified in polynomial time. Although it has not been proven, NP-hard problems are believed to have no polynomial-time algorithms.

Smart charging objectives can be achieved by charging control techniques over a single-decision time horizon or over a finite length decision-time horizon, $\mathcal{T} := \{1, 2, \ldots, T\}$.

In a single-deadline charging scheduling problem, the optimization algorithm decides whether an EV is charged or not at each decision time, t, until the next one, $t + 1$, which is equivalent to the optimization problem of selecting a subset of EVs to be charged at time step t. this problem reduces to the *0/1 knapsack problem* in (4.1), which is known to be a classic NP-hard problem. Given a set of n items, each with weight w_i and value v_i, along with the maximum weight capacity W, the 0/1 knapsack problem maximizes the sum of the values of the items in the knapsack so that the sum of the weights is less than or equal to the knapsack's capacity.

$$
\begin{aligned}
\max \quad & \sum_{i=1}^{n} v_i x_i \\
\text{s.t.} \quad & \sum_{i=1}^{n} w_i x_i \leq W \\
& x_i \in \{0, 1\}.
\end{aligned}
\tag{4.1}
$$

By a reduction to the 0/1 knapsack problem (Equating the knapsack's maximum weight capacity to the available charging capacity, P_{max} at time t), it is argued in [54] that single-deadline charge scheduling is weakly NP-hard. In Chapter 3, we have tackled this computation problem *efficiently* by sorting the values assign to EVs using the stochastic load models.

When we try to solve the optimization problem of allocating discrete charging rates to EVs at the time step t, the problem reduces to the *bounded knapsack problem (BKP)*, which is also NP-hard [54]. BKP, in (4.2), removes the restriction that there is only one of each item, but restricts the number x_i of copies of each kind of item to a maximum non-negative integer value c.

$$
\begin{aligned}
\max \quad & \sum_{i=1}^{n} v_i x_i \\
\text{s.t.} \quad & \sum_{i=1}^{n} w_i x_i \leq W \\
& x_i \in \{0, 1, 2, \ldots, c\}.
\end{aligned}
\tag{4.2}
$$

Evidently, charging scheduling algorithms are better at fully utilizing the flexibility of EV loads in satisfying the energy demand because they optimize charging decisions over multiple time steps over a finite decision time horizon, $\mathcal{T} := \{1, 2, \ldots, T\}$. On the other hand, the optimization problem of selecting a subset of EVs to be charged at each time step $t \in \{1, 2, \ldots, n\}$ reduces to a time-expanded version of 0/1 knapsack problem where there exist $T.n$ items to choose from, which is also NP-hard [55].

4.1.2 Nonexistence of Solutions

Consider the peak-constrained charging scheduling problem given in (4.3) as a Mixed Integer Linear Problem (MILP), where the arrival/departure times and energy demand of the customers are represented with the tuple (a_i, d_i, e_i). Given enough latent flexibility, the optimum solution (or one of the optimum solutions) allocates charging times and rates such that each customer is received their requested demand, e_i. When this case is not possible, the optimum solution maximizes welfare by trying to achieve at least a critical value, $e_{i,cr}$, for each EV with the constraint in (4.3d).

$$
\begin{aligned}
\max \quad & \mathcal{U}(x) := \sum_{\substack{t\in\mathcal{T}\\ i\in\mathcal{N}}} x_i^t && && \text{(4.3a)}\\
\text{s.t.} \quad & x_i^t = 0, && t < a_i,\ t \geq d_i,\ i \in \mathcal{N} && \text{(4.3b)}\\
& r \sum_{i\in\mathcal{N}} x_i^t \leq P_{max}^t, && t \in \mathcal{T} && \text{(4.3c)}\\
& e_{i,cr} \leq r \sum_{t\in\mathcal{T}} x_i^t \leq e_i, && i \in \mathcal{N} && \text{(4.3d)}\\
& x_i^t \in \{0, 1\}, && t \in \mathcal{T},\ i \in \mathcal{N} && \text{(4.3e)}
\end{aligned}
$$

The lower bound in (4.3d) causes an infeasible constraint set when:

1. The duration between a_i and d_i is not adequate to achieve $e_{i,cr}$ even with non-stop charging for a certain EV in $\mathcal{N}$,
2. The set of $\mathcal{P} := \{P_{max}^1, P_{max}^2, \ldots, P_{max}^T\}$ prolongs the time necessary for charging multiple EVs together restraining at least one EV to achieve $e_{i,cr}$ before its d_i. In this chapter, we devise a quadratic optimization function utilizing the stochastic demand to discard the lower bound in (4.3d).

4.1.3 Literature Review of Charging Scheduling Algorithms

The objective of EV charging control shows diversity depending on the operator's standpoint. Hence, many studies are addressing the first challenge [56]. In [57], two efficient scheduling algorithms for centralized and distributed charging are proposed to balance congestion between different charging stations and maximize the welfare. Reference [55] tackles the computational hardness of the scheduling problem with a low-complexity primal-dual scheduling algorithm in the offline scheduling case and devises a competitive algorithm design for the online case. Competitive algorithm designs find optimal charging solutions without exact or stochastic information about the future EV arrival [48]. A method for scheduling charging and discharging of electric vehicles, which is based upon the identification of joint time intervals and the optimal number of charge and discharge time intervals, is presented in [58]. These works rely on only causal information on the EV demand, optimizing the load demand revealed at the current time but possibly underestimating the load demand revealed in the future.

4.2 Charging Scheduling Method for Workplace Charging Stations

Uncertainty and randomness of future knowledge are challenges for online charging scheduling, which can be reduced by utilizing stochastic EV load models. In this section 4.2, the single system-time horizon coordinated charging control algorithm in 3 is extended to a multi-objective scheduling algorithm considering a finite system-time horizon. The scheduling algorithm makes assumptions about the future arrivals to the charging station, unlike the classical online EV charging scheduling algorithms, which optimize the load demand revealed at the current time but underestimate the load demand revealed in the future. Therefore, EV load models are utilized in a model predictive control based approach to decrease the complexity of the stochastic online charging problem into a deterministic case.

4.2.1 System Description

We consider a private workplace parking lot with a single charging station. The users of the parking lot are required to be registered to the system to benefit from the charging infrastructure, enabling the CPO to know the set of EVs visiting the charge point (CP). $\mathcal{N} := \{1, 2, \ldots, N\}$ is the set of EVs over the decision-time horizon T. We use a discrete time model, with time indexed by $t \in \mathcal{T} := \{1, 2, \ldots, T\}$ and the length of each time period is δ. Each EV $i \in \mathcal{N}$ described with two tuples $(a_i, d_i, e_i)^{stoc}$, (a_i, d_i, e_i), stochastic and actual values.

The charging scheme assumes adequate number of plugs for all EVs present in the parking space of the corporate complex. A subset of plugs are energized at a given time, $t \in \mathcal{T}$, when the system's capacity is tight for satisfying the charging demand, or the maximum number of EVs charged simultaneously is retrenched on purpose to shave the peak EV demand by limiting it with $\mathcal{P} := \{P^1_{max}, P^2_{max}, \ldots, P^T_{max}\}$. We assume that EVs are charged by the Electric Vehicle Supply Equipment (EVSE) they are connected to with allocated rates at all times. For simplicity, a single charging rate, r, is used for all EVs.

In general, charging stations are controlled in a hierarchical manner in which the system parameters and constraints such as the VRE availability and current limits in a given time are specified for the scheduling algorithm by a controlling unit/agent with higher status in the hierarchical order. Although the EV loads and other DERs in the system can be controlled in a centralized manner as in smart homes, this is hardly suitable for controlling commercial charging stations, considering the number of vehicles to be charged. In centralized control, system agents (each EV connected to the station, PV units, dispatchable and critical loads, diesel generator, etc.) are controlled by a centralized controller, which implies that all parameters related to these agents must be considered by a single optimization algorithm.

The station's maximum allowable total charging demand, $\mathcal{P} := \{P^1_{max}, P^2_{max}, \ldots, P^T_{max}\}$ is assumed to be given. Moreover, the per unit revenue for charging and electricity cost are assumed to be constant.

4.2.2 Online Charging Scheduling Algorithm

In this section, we formulate the peak-constrained charging scheduling as a mixed integer problem (MIP) and devise an event-triggered multi-objective online scheduling algorithm. The proposed solution utilizes EV load models in a model predictive control based approach to reduce the complexity of stochastic online charging problem into a deterministic case.

$$
\begin{aligned}
\min \quad & \mathcal{U}(t, x, y) && && \text{(4.4a)} \\
\text{s.t.} \quad & x_i^t = 0, && t < a_i,\ t \geq d_i,\ i \in \mathcal{N} && \text{(4.4b)} \\
& r \sum_{i \in \mathcal{N}} x_i^t \leq P_{max}^t, && t \in \mathcal{T} && \text{(4.4c)} \\
& r \sum_{t \in \mathcal{T}} x_i^t = y_i, && i \in \mathcal{N} && \text{(4.4d)} \\
& y_i \leq e_i, && i \in \mathcal{N} && \text{(4.4e)} \\
& x_i^t \in \{0, 1\}, && t \in \mathcal{T},\ i \in \mathcal{N} && \text{(4.4f)}
\end{aligned}
$$

The scheduling problem in (4.4) is quite similar to the MILP formulation in (4.3). Here, the lower bound in (4.3d) is discarded and y_i is the total amount of energy delivered to EV $i \in \mathcal{N}$ in (4.4e), bounded by the total amount of energy requested by the EV in (4.4e).

The utility function, $\mathcal{U}$, in (4.4a) formulated by (4.5). $\mathcal{U}_1$ in (4.5b) improves the fairness of allocated charging times. There can be more than one optimal solution to charge all EVs at their requested demand, given enough latent time flexibility for the scheduling jobs. Therefore, $\mathcal{U}_2$, in (4.5c) is added to the objective function so that EVs are charged as quickly as possible. This objective function is utilized in other scheduling problems than EV scheduling, such as computing job scheduling and industrial process optimization to find the solution with the minimum total operation time. The α constants in (4.5a) tune the function.

$$
\begin{aligned}
\mathcal{U} &:= \alpha_1 \mathcal{U}_1 + \alpha_2 \mathcal{U}_2 && \text{(4.5a)} \\
\mathcal{U}_1 &:= \sum_{i \in \mathcal{N}} (f_{v,i} - y_i)^2 && \text{(4.5b)} \\
\mathcal{U}_2 &:= \sum_{\substack{t \in \mathcal{T} \\ i \in \mathcal{N}}} (t - T) x_i^t && \text{(4.5c)} \\
& && \text{(4.5d)}
\end{aligned}
$$

The value functions in Chapter 3 are the inspiration for the formation of the quadratic objective function in (4.5b). In order to provide a fair distribution of charging time over the decision horizon T; the scheduling problem should prioritize delivering $e_{i,cr}$ for each EV while considering the time it takes to reach e_i. The derivative of f_v in (4.6a) decreases as the total amount of energy delivered to an EV increases making each additional charging decision less valuable than the previous one for the same EV. However, it should be noted that group constants in (4.6b) should be selected as $v_g^1 > v_g^2$ to prioritize delivering $e_{i,cr}$ and larger than 1 to prevent negative in the square function.

$$f_{v,i} = \sum_{j=1}^{e_i/r} (v_g^j + tanh(\frac{e_i - jr}{e_i})) \tag{4.6a}$$

$$v_g^j = \begin{cases} v_g^1 & , jr \leq e_{i,cr} \\ v_g^2 & , jr > e_{i,cr} \end{cases} \tag{4.6b}$$

The online charging scheduling algorithm makes assumptions on the future arrival and departure times with a_i^{stoc} and d_i^{stoc}. For a given time, $t \in \mathcal{T}$, the online scheduling algorithm assumes a_i^{stoc} and d_i^{stoc} as connection and departure times for the EVs that are not yet to be at the charging station whose energy demand is e_i^{stoc}. So, unrealistic time slots are prevented in the future for the EVs that are actually connected to the station. Similarly, the algorithm assumes that the present EVs in the charging station will depart at d_i^{stoc}. If the departure time, d_i, defined by the EV owner is earlier than d_i^{stoc}, d_i^{stoc} is reassigned as in (4.7).

$$d_i^{stoc} \leftarrow d_i \quad , d_i \leq d_i^{stoc} \tag{4.7}$$

$e_{i,cr}$ is given by the stochastic EV load models, thus $e_{i,cr} = e_i^{stoc}$. The last two assumptions enable the algorithm to associate EVs with values using (4.6) so that $e_{i,cr}$ could be delivered until d_i.

The algorithm is triggered by the occurrences of the following events in $\mathcal{E}$ and the optimization problem formulated by the MIP in (4.4) is solved for the optimal charging schedule:

- Arrival of a new EV,

- Departure of an EV,
- No arrival of an absent EV until a_i^{stoc},
- No departure of a present EV after d_i.

In the cases of the last two items in the event list, the online charging scheduling algorithm makes the new assumptions about the future arrival and departure times and reassigns a_i^{stoc} and d_i^{stoc} according to (4.8).

$$a_i^{stoc} \leftarrow t+1 \quad , a_i^{stoc} \leq t < a_i \tag{4.8a}$$

$$d_i^{stoc} \leftarrow t+1 \quad , d_i \leq t \tag{4.8b}$$

The pseudo code of the online charging scheduling algorithm is given in Algorithm 2.

Profit Maximization and Cost Minimization: One of the most common objectives of charging scheduling optimization is to maximize the CPO's profit or minimize the system cost, which is achieved by following the VRE availability (if the system possesses on-site generation such as a PV system) and time-varying cost of electricity. To account for the system loads and renewable generation P_{load}^t and P_{gen}^t must be predicted for the future $t \in \mathcal{T}$ using prediction methods. Thus, two related vectors, $P_{load}^t \in \mathcal{P}_{load} := \{P_{load}^1, P_{load}^2, \dots, P_{load}^T\}$ and $P_{gen}^t \in \mathcal{P}_{gen} := \{P_{gen}^1, P_{gen}^2, \dots, P_{gen}^T\}$, are provided to the optimization algorithm as parameters. In addition, time-varying per unit electricity price, $\mathcal{C} := \{c^1, c^2, \dots, c^T\}$, the per unit revenue of the CPO for charging, $\Pi := \{\pi^1, \pi^2, \dots, \pi^T\}$, must be known. Then, the utility function, $\mathcal{U}_3$ in (4.9) can be included into the multi-objective utility function in (4.5a) to obtain $\mathcal{U} := \alpha_1\mathcal{U}_1 + \alpha_2\mathcal{U}_2 + \alpha_3\mathcal{U}_3$, where α_3 is negative.

$$\mathcal{U}_3 := \sum_{t\in\mathcal{T}} \pi^t P_{cs}^t - \sum_{t\in\mathcal{T}} c^t P_{net}^t \tag{4.9}$$

In (4.9), total charging power of the station, P_{cs}^t, and the net power consumption of the system, P_{net}^t, are calculated using (4.10) and (4.11), respectively.

Algorithm 2: Online charging scheduling algorithm

System inputs : $\mathcal{P} := \{P_{max}^1, P_{max}^2, \ldots, P_{max}^T\}$

User-defined inputs: (a_i, d_i, e_i) for $i \in \mathcal{N}$

Stochastic inputs : $(a_i, d_i, e_i)^{stoc}$ for $i \in \mathcal{N}$

Initialization:

    for $i \in \mathcal{N}$ **do**

        $(a_i, d_i, e_i) \leftarrow (a_i, d_i, e_i)^{stoc}$

        Calculate $f_{v,i}$ using (4.6a)

        $\widehat{\mathcal{N}}$ = { }

        $x_i^t = 0, t \in \mathcal{T}$

    end

if *An event in* $\mathcal{E}$ *occurs* **then**

    for $i \in \mathcal{N}$ **do**

        if $a_i^{stoc} \leq t < a_i$ **then**

            $a_i^{stoc} \leftarrow t + 1$

        end

    end

    $\widehat{\mathcal{N}} \leftarrow$ The set of arrived EVs

    for $i \in \widehat{\mathcal{N}}$ **do**

        $(a_i, d_i, e_i) \leftarrow (a_i, d_i, e_i - r \sum t x_i^t)$

        if $d_i \leq d_i^{stoc}$ **then**

            $d_i^{stoc} \leftarrow d_i$

        end

        Calculate $f_{v,i}$ using (4.6a)

        if $d_i \leq t$ **then**

            $d_i^{stoc} \leftarrow t + 1$

        end

    end

    Solve (4.4) with $(a_i^{stoc}, d_i^{stoc}, e_i)$, $i \in \mathcal{N}$

    for $i \in \widehat{\mathcal{N}}$ **do**

        Set the plot signal of EV to $r.x_i^t$ for $t \in \{t, t+1, \ldots, T\}$

    end

end

$$P_{net}^{t} = P_{cs}^{t} + P_{load}^{t} - P_{gen}^{t} \quad , t \in \mathcal{T} \tag{4.10}$$

$$P_{cs}^{t} = r \sum_{i \in \mathcal{N}} x_{i}^{t} \quad , t \in \mathcal{T} \tag{4.11}$$

When $\pi^t \in \Pi$ is nonzero, the utility function, $\mathcal{U}_3$, maximizes the profit; otherwise, when π^t is zero, it minimizes the electricity cost of the system. Since both the per unit revenue for charging and electricity cost are assumed to be constant, $\mathcal{U}_3$ has no effect on the optimum schedule, which is why it is omitted in (4.4a).

4.2.3 Simulations

This subsection presents a comparison between the offline charging solution based on the stochastic EV models, $(a_i, d_i, e_i)^{stoc}$, and the online charging scheduling solution. In the offline solution $(a_i, d_i, e_i)^{stoc} = (a_i, d_i, e_i)$ since it is based on the predicted parameters. Table 4.1 presents the tuples describing the EVs in $\mathcal{N} := \{1, 2, \ldots, 7\}$ in this charging scenario. The system allows the simultaneous charging of at most three vehicles, and the charging rate, r, of each EVSE is 1.84 kW.The length of each time period, δ, is 15 minutes. e_i is selected observably greater than the stochastic demands to demonstrate the differences between the offline and online solutions. Also, the actual arrival time of EV 6 is selected significantly later than its predicted value to include an extreme event in the simulation.

Table 4.1: Actual and stochastic EV model parameters used in the scheduling algorithm

EV	a_i	d_i	e_i (kWh)	a_i^{stoc}	d_i^{stoc}	e_i^{stoc} (kWh)
1	07:30	16:45	8.74	09:30	16:00	6.9
2	09:15	18:00	11.04	10:15	17:00	8.28
3	07:45	16:45	5.52	09:15	16:30	4.14
4	07:45	18:15	7.36	09:15	17:00	5.52
5	06:45	17:15	5.52	08:15	16:45	4.14
6	14:15	17:00	4.6	09:45	16:30	2.76
7	07:30	16:30	11.96	09:45	16:15	9.66

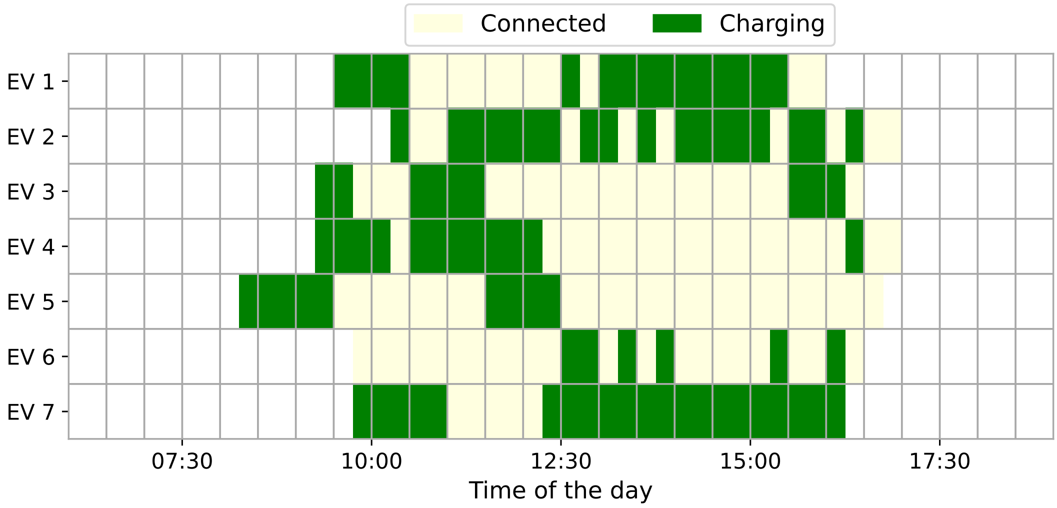


Figure 4.1: Offline charging scheduling solution based on stochastic EV models

The offline charging solution based on the stochastic EV models, $(a_i, d_i, e_i)^{stoc}$, is given in Fig. 4.1 while the online charging scheduling solution is presented in Fig. 4.2.

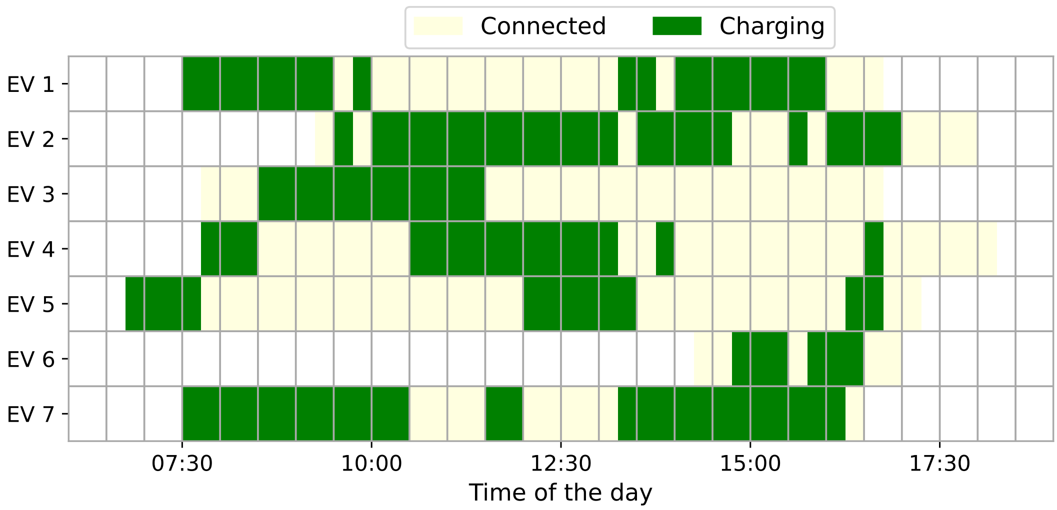


Figure 4.2: Online charging scheduling solution with stochastic EV models

Similar to the the coordinated charging algorithm in Chapter 3, the charging scheduling algorithm stretches the morning peak over a more extended period. Fig. 4.3 compares the total charging demands of offline and online charging scheduling solutions and the total demand if no charging control is implemented.

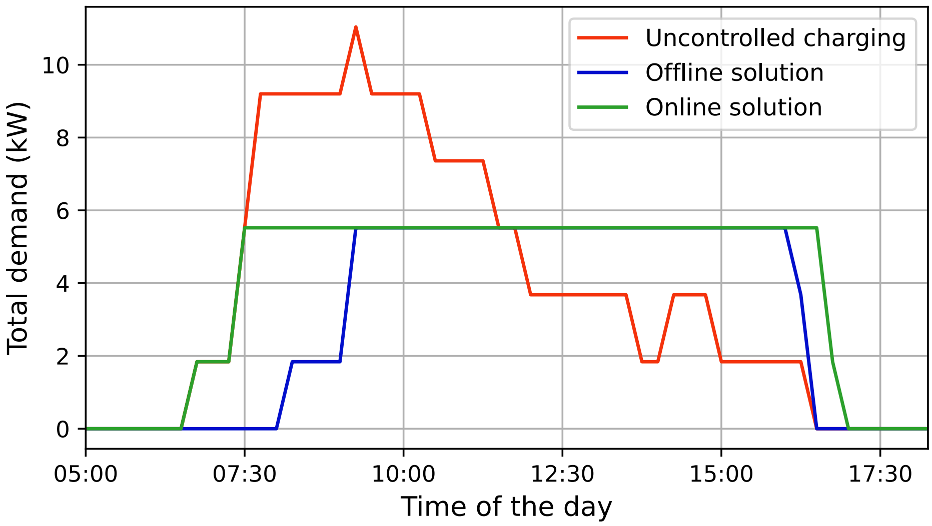


Figure 4.3: Total charging demands of uncontrolled charging, offline and online charging solutions.

4.3 Conclusion

Motivated by the rapid proliferation of customized experiences based on past user data in the service industry, this chapter studied charging scheduling using individual EV load models for a company's parking lot. This work assumes there are an adequate number of plugs for all EVs in $\mathcal{N} := \{1, 2, \ldots, N\}$ over the decision-time horizon T. Moreover, it assumes that the individual load model for each customer that visits the charging station is available since the online charging scheduling algorithm is designed for workplace charging at a private parking lot.

In large scale AC smart charging stations, the charging profiles of each customer, (a_i, d_i, e_i), is usually set by the EV owner through a mobile application [20]. Classic online charging scheduling algorithms rely on causal information since the connection duration and energy demand defined by the future customers are unavailable until their arrival at the station. Thus, these scheduling algorithms optimize the load demand revealed at the current time but underestimate the load demand revealed in the future [48].

In this chapter, stochastic EV load models are utilized to complement the optimization function of the scheduling process by extending the degree of knowledge of future random data. The charging scheduling algorithm in Section 4.2, formulated as MIP with a quadratic optimization function of the values calculated from the EV load models, makes assumptions on load demand revealed in the future based on the EV models. Moreover, this algorithm acknowledges the variance in the flexibility of each driver's departure times and utilizes this information to improve the fairness of charging time allocation to ensure each EV is charged at least a critical amount.

CHAPTER 5

CONCLUSION AND FUTURE WORK

Since the declaration of the Green Deal in 2019, reducing greenhouse gas emissions to achieve carbon neutrality and limit the rise in global temperature has become a race against global warming in Europe. As of the end of 2021, Turkey also set out to fulfill its obligations regarding the global climate crisis, in line with the EU's climate neutrality target, which includes the electrification of end-use sectors, including the transportation sector. This transformation requires demand-side flexibility through sector coupling flexibility resources to the end-use sectors. This thesis concerns one of these solutions, the coupling of smart AC charging algorithms to commercial charging stations for safer EV adoption. In particular, this thesis studied the utilization of individual EV load models based on KDE and the employment of these models in real-time AC charging control for a private parking lot.

5.1 Summary of the Contributions

The main contributions are the following:

- An extensive overview of the cyber-physical EV charging ecosystem is provided in Chapter 2 to alleviate confusion on the standards and protocols applied to EV charging infrastructure.
- The necessity of modeling the EV drivers separately is shown by investigating the CDFs of the random variables describing individual EV loads in Chapter 3.
- Through the simulations in Chapter 3, it is shown that acknowledging the vari-

ance in the flexibility of each driver's demand improves the fairness of charging time allocation to ensure each EV is charged at least a critical amount.

- Two coordinated charging algorithms utilizing the individual EV load models are proposed:
  - The coordinated charging algorithm in Chapter 3 tackles the NP-hardness of single-deadline scheduling *efficiently* by sorting the values assigned to PEVs using the stochastic load models,
  - The scheduling algorithm in Chapter 4 utilizes a quadratic optimization function of the values calculated from the EV load models. Thus, EV load models in a model predictive control based approach here to decrease the complexity of stochastic online charging problem into a deterministic case.
  - The scheduling algorithm in Chapter 4 makes assumptions about the future arrivals to the charging station, unlike the classical online EV charging scheduling algorithms, which optimize the load demand revealed at the current time but underestimate the load demand revealed in the future.

5.2 Practical Limitations and Future Work

In this work, the random variables describing the arrival and departure times of the EVs are estimated using KDE. The mean of the energy requested from the charging network for a simple stochastic representation of the charging demand. The KDE method can be used to estimate the charging amount provided to the EV by a specific charging station, assuming the charging amount of each session is recorded. There are multiple aspects to consider for estimating the charging amount, such as daily routes, traffic congestion, and other charging points visited by the driver. This work assumes that drivers follow the same course in their everyday commutes under similar traffic congestion levels.

The findings put forward the advantages individual load models provide in smart charging algorithms. However, there is a trade-off between the details an algorithm can contemplate and storage and computational costs. The simulations include only seven different drivers. Investigating the scalability of the strategies used in this work as the number of drivers increases should be the follow-up work on this thesis work.

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