SOCIO-ECONOMIC ANALYSIS OF INCREASED EV CHARGING LOADS ON LMPS AND DLMPS

A Thesis

by

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Submitted to the
Graduate School of Sciences and Engineering
in Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in the
Deparment of Electrical & Electronics Eng.

Özyeğin University
August 2024

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To me and my beloved family...

ABSTRACT

The increasing adoption of electric vehicles (EVs) introduces significant time-variant electrical energy demand, adding complexity to traditional electricity markets. This thesis explores the impacts of EV charging load on locational marginal pricing (LMP) and distribution locational marginal pricing (DLMP). In the first part of the study, an economic dispatch model is used to analyze the effects of time-variant EV charging load on LMP within the IEEE 39-bus system. Scenarios consider the spatial distribution of EVs, revealing that strategic placement of EV charging stations can mitigate economic impacts on end-users. The second part examines the effects of uncoordinated EV charging on DLMPs through a multi-period alternating current (AC) optimal power flow analysis on a modified IEEE 34-bus system. Results show that DLMPs are most affected during peak hours, with AC charging proving more economical; moreover, battery integration can enhance social welfare. This thesis provides valuable insights for policymakers and stakeholders in managing the transition to electrified transportation, ensuring grid reliability and economic efficiency through strategic EV integration and optimized charging infrastructure.

Keywords: Electric Vehicles, Locational Marginal Pricing, Distribution Locational Marginal Pricing, Cost-to-Load Analysis, Electricity Markets.

ÖZETÇE

Elektrikli araçların (EA) artan adaptasyonu, geleneksel elektrik piyasalarına zaman-değişkenliğinde büyük ölçüde elektrik enerjisi talebi ekleyerek karmaşıklık katmaktadır. Bu tez, EA şarj yükünün bölgesel marjinal fiyatlandırma (BMF) ve dağıtım bölgesel marjinal fiyatlandırma (DBMF) üzerindeki etkilerini araştırmaktadır. Çalışmanın ilk bölümünde, zaman değişkenliğinde EA şarjının LMP üzerindeki etkilerini analiz etmek için ekonomik yük dağıtım modeli kullanılmıştır. Senaryolar, EA'ların mekansal dağılımını dikkate alarak, EA şarj istasyonlarının stratejik yerleştirilmesinin son kullanıcılar üzerindeki ekonomik etkileri azaltabileceğini ortaya koymaktadır. İkinci bölümde, düzensiz EA şarjının DLMP'ler üzerindeki etkileri, modifiye edilmiş IEEE 34-bus sistemi üzerinde çok dönemli alternatif akım (AC) optimal güç akışı analizi ile incelenmiştir. Sonuçlar, DLMP'lerin en çok pik saatlerde etkilendiğini, AC şarjının daha ekonomik olduğunu ve batarya ile entegre olduğunda sosyal refahı artırdığını göstermektedir. Bu tez, elektrikli ulaşıma geçişi yönetmede politika yapıcılar ve paydaşlar için şebeke güvenilirliğini ve ekonomik verimliliği hedefleyen stratejik EA entegrasyonu ve şarj altyapısı optimizasyonu konularında değerli içgörüler sağlamaktadır.

Anahtar Kelimeler: Elektrikli Arabalar, Bölgesel Marjinal Fiyatlandırma, Dağıtım Bölgesel Marjinal Fiyatlandırma, Yük Maliyeti analizi, Elektrik Piyasaları.

ACKNOWLEDGEMENTS

First and foremost, I want to thank myself for completing this journey to the end. If I were to take a look at myself applying for a master's degree from where I am now, I would see me who does not know what I have accomplished and how I have pushed my own limits. I have a long way to go, and I am just at the beginning of my adventure.

I would like to extend my deepest thanks to my advisor, who provided the foundational knowledge for this thesis topic during the first semester of my master's program and helped me build upon it every day, enabling my growth. Sometimes, amid all the things I wanted to accomplish, you helped me find my way.

I am also deeply grateful to the lovely residents of our little lab, Ahmad El Sayed, Eren Tekeler, Hilmi Namli, and my friend Eihab Ahmed, who started and finished the master's program with me. Without your help, I would have been overwhelmed by the workload.

My sincere love and gratitude go to my dear family, who have supported my passion for learning and my love for learning since my elementary school years.

Lastly, I want to express my appreciation to my beloved and our cat, who witnessed all the ups and downs in the background over these past two years, always tried to support me, and never left me alone. Please continue to be my support team as I plan to continue my academic journey with a Ph.D.

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LIST OF ABBREVIATIONS

Abbreviation	**Definition**
AC	Alternating Current
AC OPF	Alternating Current Optimal Power Flow
BEV	Battery Electric Vehicle
BEMS	Battery Energy Management System
BO	Build-Operate
BOT	Build-Operate-Transfer
DAM	Day-Ahead Market
DC	Direct Current
DC OPF	Direct Current Optimal Power Flow
DER	Distributed Energy Resources
DG	Distributed Generator
DLMP	Distribution Locational Marginal Pricing
ED	Economic Dispatch
EV	Electric Vehicle
EVC	Electric Vehicle Charging
EVCS	Electric Vehicle Charging Stations
EXIST	Energy Exchange Istanbul
HEV	Hybrid Electric Vehicle
IDM	Intra-day Market
IoT	Internet of Things
IP	Integer Programming
KKT	Karush-Kuhn Tucker

Abbreviation	**Definition**
LMP	Locational Marginal Pricing
LP	Linear Programming
MCP	Marginal Clearing Price
NLP	Non-Linear Programming
OPF	Optimal Power Flow
OTC	Over-the-Counter
PHEV	Plug-in Hybrid Electric Vehicle
RES	Renewable Energy Sources
SMP	System Marginal Price
UC	Unit Commitment
UD	Unit Dispatch

CHAPTER I

INTRODUCTION

The growing global population has increased pressure on energy systems. Traditional power generation, which mainly depends on fossil fuels, has struggled to keep up with rising electricity demand. This heavy reliance on fossil fuels has resulted in significant carbon dioxide emissions, worsening climate change. Consequently, there's an urgent need to transition towards cleaner energy, like using renewable energy sources (RES). However, the intermittent nature of renewable energy necessitates advanced grid infrastructure capable of balancing supply and demand.

The emergence of electric vehicles (EVs) offers a promising avenue for reducing greenhouse gas emissions. Yet, the widespread adoption of EVs will significantly increase electricity consumption. This surge in demand poses challenges for power grids, requiring substantial investments in infrastructure and grid management. A comprehensive approach is essential to fully harnessing the environmental benefits of EVs while ensuring grid reliability. This involves integrating renewable energy, developing smart grid technologies, and implementing efficient charging strategies.

1.1 Electricity Supply Chain

An electric power system, commonly referred to as an electric grid, is a vast network comprising power-generating plants connected to consumer loads. This system is fundamental to the provision of electrical energy, which, as per the principle of energy conservation, cannot be created or destroyed but can only be converted from one form to another. Electrical energy, specifically, is harnessed by converting various other forms of energy into the flow of electrons.

The invention of the generator marked a significant advancement, allowing for the conversion of mechanical energy into electrical energy. Generators produce both alternating current (AC) and direct current (DC); however, AC generators are predominant in modern power systems. Over the past two hundred years, the use of electrical energy has grown significantly because of its versatility and many applications. As electricity demand keeps increasing, it is essential to generate the exact amount needed at the moment since storing large amounts of electrical energy for later use is not practical.

The generation of electrical energy occurs simultaneously with its consumption, and electricity demand is constantly fluctuating. Consequently, electricity generation must continuously adapt to meet these varying demands. The network of lines connecting the power generation stations to the consumers of electric power is divided into two main systems: the transmission system and the distribution system. These can be further categorized; however, it is important to note that not all steps illustrated in a typical power supply scheme, such as Figure 1, are present in every power system.

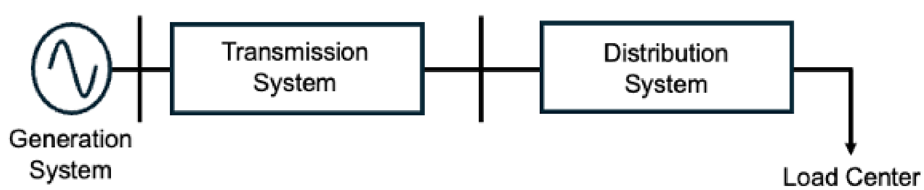

Figure 1: Supply chain of a power system.

The objective of an electric power system is to generate electricity and efficiently deliver it to the end-user in a usable form. This process typically comprises several stages: electricity generation, primary transmission, secondary transmission (if applicable), primary distribution, and secondary distribution. These stages are crucial in ensuring that electricity reaches consumers at the appropriate voltage, frequency, and reliability levels. However, in some networks, the secondary transmission stage may be absent, especially in smaller systems prioritizing direct distribution to consumers.

Generation refers to the conversion of various forms of energy into electrical energy. Transmission involves transporting this energy over long distances at high voltage levels, and distribution ensures that consumer demand is met at regulated voltage levels through feeders, which are smaller segments of load distributed across different locations.

1.1.1 Electricity Generation

The site where generators produce electric power is referred to as a generator station or power plant. Typically, the generating voltage of a regular power plant ranges from 11 kV to 13 kV. However, for economic efficiency, it is favorable to step up this produced voltage to 132 kV, 220 kV, or even 500 kV using step-up power transformers. Power plants operate continuously, producing power at different voltage and power levels based on the type of station and the generators employed.

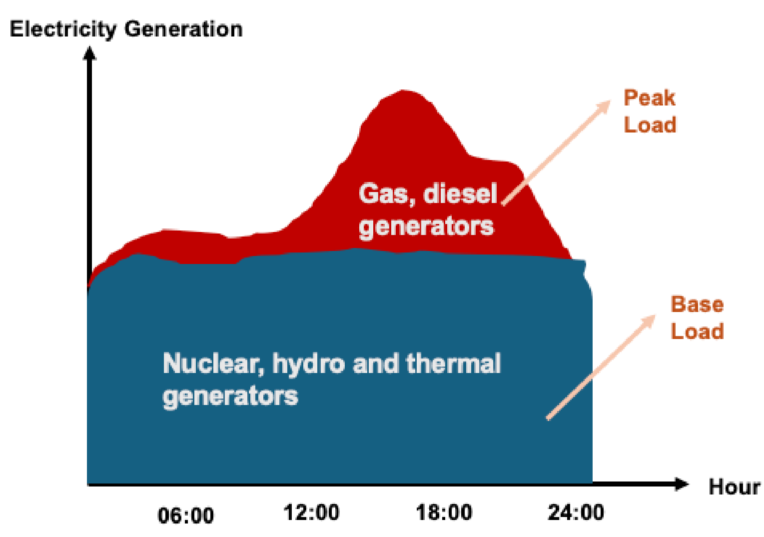

Figure 2: Combination of generation resources to meet changes in demand.

Currently, the primary types of generating stations that are employed worldwide include thermal, hydroelectric, nuclear, diesel, gas, solar, tidal, and wind power plants.

These plants generate electrical energy at various voltage levels and locations, depending on their specific type and purpose. They are categorized based on their operational roles within the power system: base load plants, which handle the consistent demand, and peak load plants, which address the fluctuating demand. For instance, thermal, hydroelectric, and nuclear plants are typically used for base load due to their longer startup times, whereas gas and diesel plants are utilized for peak load due to their rapid startup capabilities. This classification, shown in Figure 2, is essential to ensure that electricity production can meet demand instantly and maintain the reliability of electricity supply.

1.1.2 Transmission of Electricity

Electricity is transmitted at high voltage levels (such as 132 kV, 220 kV, 500 kV, or higher) to load centers using a three-phase, three-wire overhead transmission system, also called a delta connection. The voltage produced typically ranges from 11 kV to 20 kV, whereas the demand occurs at various voltage levels and often at great distances from the power generation source. Thus, the transmission system is essential for efficiently delivering electrical energy over long distances.

As the power system has expanded and demand increased, the complexity of the process has grown. At lower voltage levels, meeting high demand requires a significant current, leading to substantial voltage drops due to the resistance and reactance of the transmission lines. This causes higher transmission losses and a decrease in voltage at the endpoint, impacting both the system's cost and the performance of consumer equipment. To address these issues, transformers are used to step up the voltage to levels between 220 kV and 765 kV, thereby reducing the current for the same load and minimizing losses associated with higher current levels.

1.1.3 Distribution of Electricity

Electric supply for heavy-load consumers, such as industrial facilities, is typically provided at a demand level of 11 kV through a three-phase, three-wire overhead system. These consumers often establish separate substations to utilize the high power required for their operations. For larger-scale heavy-load consumers, the demand may be up to 132kV or 33kV. In these cases, the electric supply is provided directly by secondary transmission or primary distribution at voltages of 132 kV, 66 kV, or 33 kV, and then it is stepped down using transformers in their own substations for utilization.

As transmission lines get closer to demand centers, voltage levels are reduced to facilitate practical distribution across various load locations. Substations are equipped with numerous control mechanisms to ensure controlled and continuous power delivery with minimal disturbances. These substations distribute power to smaller units known as feeders, using either overhead lines or underground cables. Feeders serve towns, cities, or groups of industries, converting voltage levels according to specific usage requirements.

1.1.4 Classification of Distribution System Connections

Effective classification of distribution system connections is crucial as it determines operational efficiency and impacts grid reliability and performance. Based on the connecting type, there are two methods for the distribution system:

1.1.4.1 Radial Systems

In a radial distribution system, power is transmitted from the substation to various areas through separate feeders that distribute electricity in one direction only, as seen in Figure 3. This straightforward design facilitates ease of implementation and initially lower costs compared to other methods. However, its reliability is limited; if a feeder fails, the entire system may also fail.

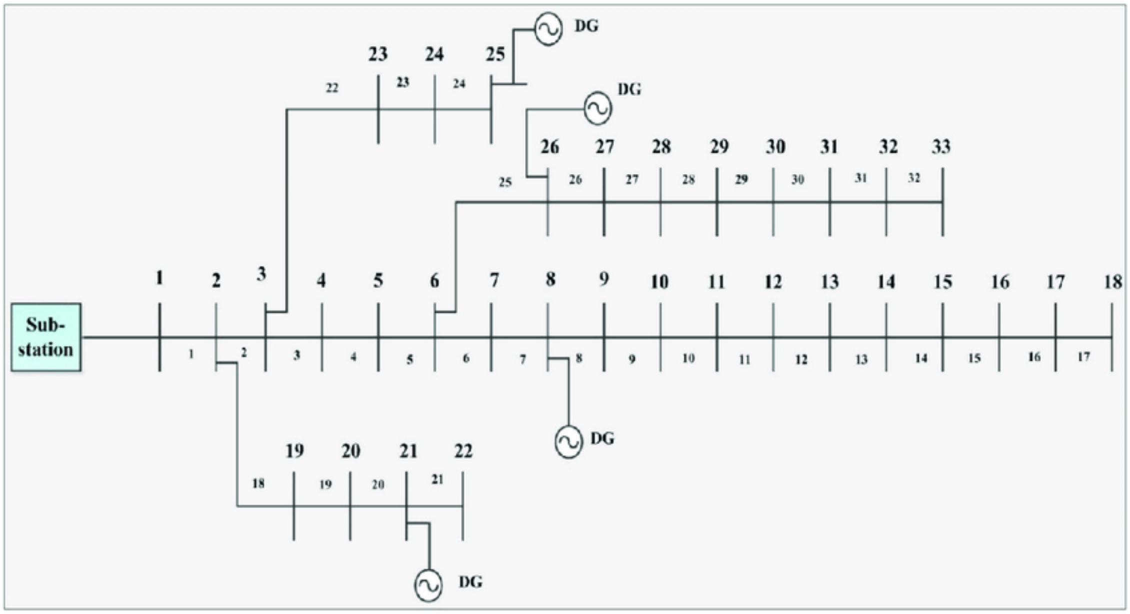

Figure 3: An illustration of a Radial system[1].

Radial systems are typically employed for short-distance distribution due to their susceptibility to voltage regulation issues, particularly affecting consumers farther from the feeder. Consequently, this configuration is predominantly used to supply power to loads located near the primary feeder, as depicted in the single-line diagram of a radial system shown above.

1.1.4.2 Loop Systems

In a loop distribution system in Figure 4, distribution transformers are connected in a loop configuration, allowing each transformer to receive power from the substation through two distinct paths. This design enhances system reliability; in the event of a fault between specific points, only the affected segment isolates while power continues to flow through the alternate path from the substation. Moreover, this design minimizes voltage fluctuations and reduces the current load on each section of the loop.

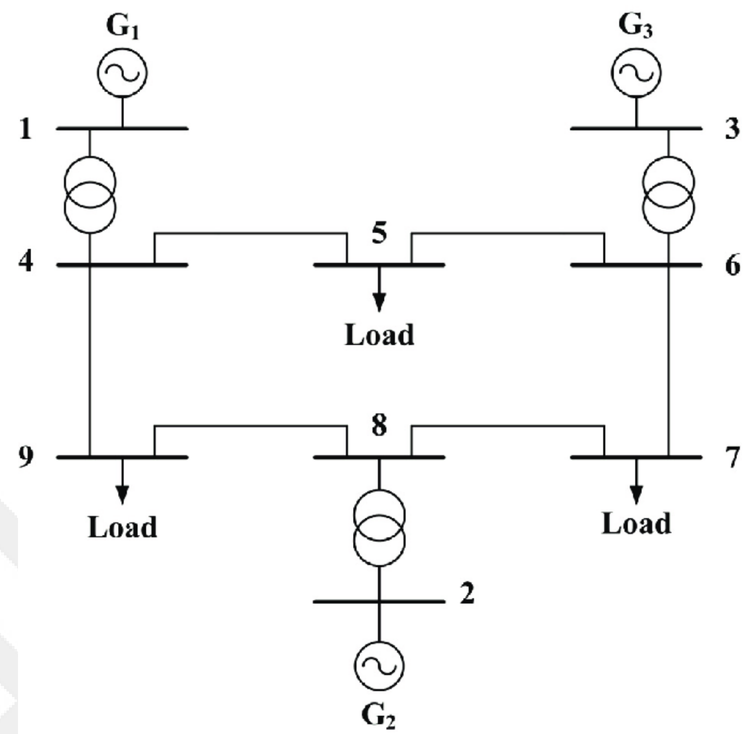

Figure 4: An illustration of a Loop system[2].

1.2 Smart Grid

The development of the electricity grid began with the installation of the first AC power grid system in Great Barrington, Massachusetts, in 1886 [3]. Initially, the grid operated as a centralized, unidirectional system of electric power transmission and distribution, driven by demand. Over the 20th century, local grids expanded and interconnected for economic and reliability reasons, evolving into highly interconnected systems with large central power stations. From the 1970s to the 1990s, increasing demand and the spread of power stations led to challenges in supply and reliability. In the 21st century, technological advancements and environmental concerns prompted the development of smart grids, enabling complex control systems to integrate RESs and enhance grid resilience.

The smart grid concept is defined through various official definitions, such as those provided by the United States' Energy Independence and Security Act of 2007 and the

European Union Commission Task Force for Smart Grids [3]. In the U.S., the smart grid is characterized by ten features, including increased use of digital technology for improved reliability and efficiency, integration of distributed and renewable resources, demand response, and smart technologies for metering and communication. The European Union defines a smart grid as an electricity network that efficiently integrates the behavior and actions of all users to ensure a sustainable, low-loss, high-quality, and secure power system. Both definitions emphasize the integration of digital processing and communication, making data flow and information management central to the smart grid's operation.

The smart grid enhances the traditional electrical grid by incorporating two-way communications and distributed intelligent devices. This bidirectional flow of electricity and information improves the delivery network's efficiency and reliability. Smart grid technology enables numerous advancements, including demand-side management and integration of variable renewable energy sources like solar and wind power. The smart grid represents a comprehensive approach to addressing electricity supply challenges, leveraging advanced technologies to enhance energy infrastructure flexibility and efficiency.

1.2.1 Differences Between Smart and Traditional Grid

Smart grids integrate RESs to emphasize sustainable growth and development while minimizing environmental impact. Traditional fossil fuel-based power generation technologies significantly endanger global environmental health. Moreover, the conventional grid lacks the capacity to manage the increased penetration of RESs effectively. In contrast, smart grid technologies can be locally installed with relatively low investment, thereby reducing transmission costs. A comparison of the most significant differences between the traditional grid and the smart grid is given in Table 2. [4].

Table 1: Comparison of features between the conventional grid and the smart grid.

Features	**Conventional Grid**	**Smart Grid**
Complexity	less complex.	more complex.
Bi-directional communication	not possible.	involves efficient system through advanced devices
Capability of self-healing and self-restoration	does not have the capability.	have capability to restore automatically.
Consumer activeness	consumers are not allowed to be involved.	allows consumer involvement.
Real-time pricing	does not have a real-time pricing mechanism.	allows real time pricing through metering devices.
Advanced control and measurement	does not have these mechanisms.	has the latest automation.
Penetration of Renewable Energy Resource and Distributed Generator	does not efficient DGs and RESs penetration.	efficient operation of DGs and RESs,
Electric Vehicle, Energy Storage System	does not allow EVs, has conventional storage.	allow EV penetration, latest storage technologies.
Advanced metering infrastructure system	does not any.	has AMI system.
Power quality	weak power quality, especially in power outages.	better power quality with automation.

The smart grid concept, in contrast to traditional grids, earns its 'Smart' designation for several key reasons [5]. First, it works on a digital platform, allowing for quick and reliable network measurements. Second, its flexible design allows it to adapt quickly to changing conditions in different areas. Third, it is resilient, staying functional despite various weather conditions and natural disasters. Additionally, it can self-repair by using real-time monitoring and proactive methods to prevent failures. Moreover, its scalability means the grid can easily adjust to changing consumer demands, handling both increases and decreases in capacity. Lastly, smart grids prioritize environmental sustainability by integrating RESs and employing technologies aimed at reducing carbon emissions alongside utilizing recyclable system components.

1.2.2 Components of Smart Grid

In contrast to traditional networks, it is essential to gather data to enable remote monitoring from the point of production through to the delivery of energy to the end user. For a system in Figure 5, data collection must be conducted from smart meters and various types of sensors. Additionally, distributed energy sources must be integrated into the system, and a comprehensive end-to-end communication infrastructure must be established.

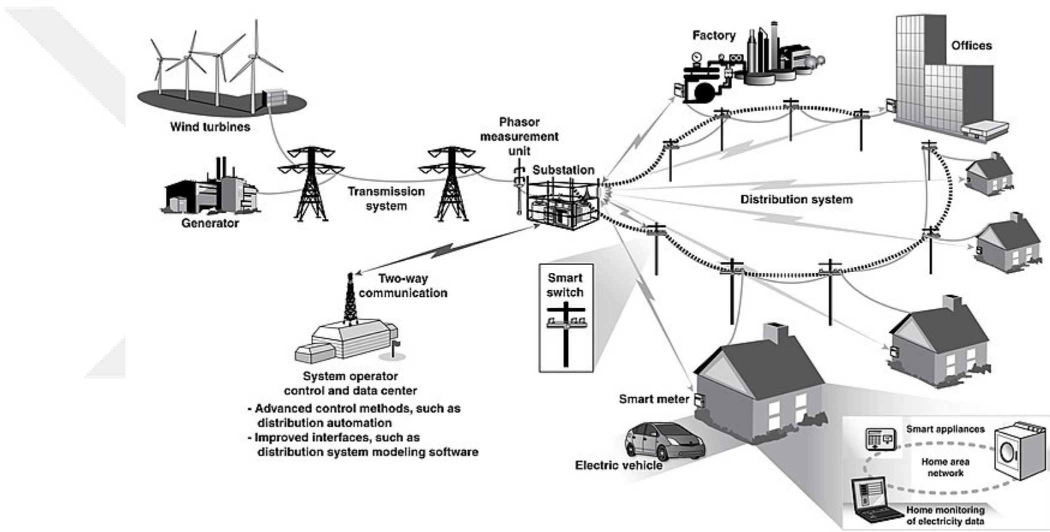

Figure 5: Common smart grid components [6].

The components of this structure, which is achieved through the integrated communication network of demand monitored through Smart Production, Smart Stations, Smart Distribution, and Smart Meters, can be listed [7]:

1.2.2.1 Smart Substations

By integrating digital technology, the various components of the substation have been enhanced and augmented to function more effectively at higher ratings with improved reliability compared to previous implementations. The primary problem lies in integrating all these components into a fully digital substation and ensuring their operation in demanding scenarios. The Internet of Things (IoT) refers to a system of interconnected devices, buildings, and various physical objects equipped with sensors linked through networks that are monitored and controlled by computer-based systems.

1.2.2.2 Sensing and Measurements

Emerging sensing and measurement technologies will promote electricity markets and facilitate more efficient energy use, helping both users and utilities save capital. These technologies are utilized to evaluate and monitor equipment health, prevent energy loss, and support control strategies.

1.2.2.3 Integrated Communication System

A main requirement for establishing a smart grid involves a dependable and high-speed integrated communication infrastructure. This system connects various components within an open architecture, enabling the collection of real-time information, control, and data exchange to optimize the security of the system while efficiently utilizing assets. An integrated communication system facilitates rapid data transmission between different transmission substations and the system control center.

1.2.2.4 Smart Meter

Meter technology facilitates a two-way communication channel between electricity providers and end users. Smart meters offer numerous advantages, such as rapid collection of billing data, detection of system failures, and faster notification to maintenance teams compared to manual systems, as utilities are informed instantaneously of any failures. These devices utilize collected data to generate revenue, detect system failures, and dispatch repair teams to precise locations more rapidly. Additionally, smart meters have real-time sensors to monitor power quality.

Table 2: Advantages and disadvantages of smart meters for consumers and electric utilities.

Advantages for 'consumers'	**Disadvantages for 'consumers'**
Provides extensive and detailed feedback on electricity utilization	Requires additional investment for installing smart meters.
Enables the adjustment of consumer routines to reduce energy bills.	Raises privacy concerns regarding the collection and use of personal data.
Reduces the frequency of blackouts and system-wide energy outages.	Increases user responsibilities for maintenance.

Advantages for 'electric utilities'	**Disadvantages for 'electric utilities'**
Removes the need for monthly manual meter readings.	Requires additional investment for employee training system construction, and data storage.
Enables real-time monitoring of the electric system.	Necessitates supervising user responses and and feedback regarding new meters.
Reduces capital investment costs for constructing generation facilities.	Ensures the safety and privacy of metered data

1.2.2.5 Smart Appliances

Smart appliances utilize advanced computer and communication techniques to perform functions more quickly, cost-effectively, and energy-efficiently. These appliances set a predefined preference level for consumers, indicating when and at what level to use electricity. By providing insight into energy generation status and minimizing peak demand factors, smart appliances significantly impact utility generators. Smart appliances can communicate with neighboring appliances to regulate energy consumption at the community level.

1.3 Electricity Markets

An electricity market is a framework that facilitates the trading of electrical energy via an electrical grid. Traditionally, companies that run electric generators have sold electricity, which has been bought by consumers or electricity retailers. The electric power industry originated in the late 19th century in the United States and the United Kingdom. Over the 20th century and continuing into the present day, the economic management of electricity has evolved significantly. These changes, driven by technological advancements in both supply and demand, as well as political and ideological factors, have appeared differently in various regions and countries. [8].

At the dawn of the 21st century, many countries restructured their electric power sectors. They moved from the traditional, vertically integrated, and heavily regulated electricity market to a more competitive structure involving separate markets for generation, transmission, distribution, and retailing. This shift marked a broader change, transforming the view of electricity from a public utility, like sewerage, to a tradable commodity, like crude oil.

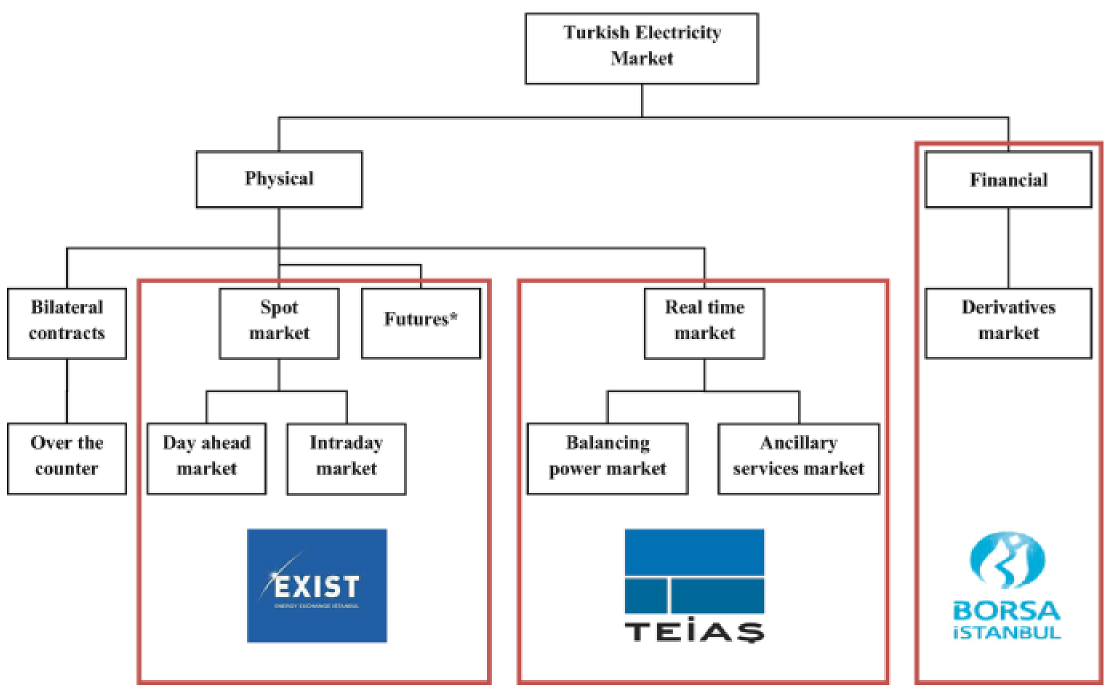

Figure 6: Electricity Markets in Turkey [9].

The liberalization of electricity production began with the Build-Operate-Transfer (BOT) and Build-Operate (BO) models, which also succeeded in attracting investors through the emerging wholesale markets. Transmission activities are carried out by TEİAŞ, a public company that owns the transmission assets [10]. In this context, TEİAŞ operates as both the system operator and market operator within the market activities domain. With the unbundling of the Turkish Electricity Authority, the market that previously had a single-buyer structure enabled supply companies and independent power producers to transact on the Market Financial Settlement Center (PMUM) platform with the implementation of the Day-Ahead Market (DAM) in 2011. The structure, where TEİAŞ undertook the role of market operator, was transferred to the Energy Markets Operation Co. (EPİAŞ) in 2015. Besides DAM, to reduce system imbalances, the Intra-Day Market (IDM) was established under EPİAŞ to ensure continuous trading. Additionally, the Balancing Power Market (BPM) is managed by TEİAŞ to handle ancillary services and system imbalances.

For electricity distribution companies that provide infrastructure services, it is critically important to resolve data-sharing issues and maintain equal distance from all suppliers to achieve the desired competitive market structure. Consequently, all 21 electricity distribution companies were privatized by 2015, further expanding the responsibilities of the private sector in electricity markets. Subsequently, distribution companies and retail companies, which were previously under the same umbrella, started operating under different legal entities.

The Turkish electricity market, as shown in Figure 6, conducts electricity trading in two main ways: non-physical and physical electricity trading. Non-physical electricity trading takes place on the electricity derivatives markets under Borsa İstanbul, while physical electricity trading is conducted through four different markets: spot markets, bilateral contracts market, futures electricity market (under EPİAŞ), and real-time markets (under TEİAŞ) [10].

1.3.1 Derivative Electricity Market

Non-physical electricity trading involves buying and selling contracts aimed at protecting market participants from potential future price risks. This trading, known as the electricity derivative markets, is operated by Borsa İstanbul. Market participants engage in these markets to hedge against potential future price risks, thus physical delivery of electricity is not involved. Electricity trading in these markets is carried out through futures contracts and options, allowing participants to hedge positions taken in spot markets. Various futures contracts, including monthly, quarterly, and yearly contracts, are available, primarily used by participants involved in electricity trading, consumption, distribution, and production, who seek to protect against price risks [11].

1.3.2 Physical Electricity Trading

The bilateral contracts market refers to electricity supply agreements prepared based on agreements between market participants. There is no central authority regulating the bilateral contracts market; instead, it operates entirely on the freedom of contract among participants, provided legal regulations are met [10]. In Turkey, the bilateral contracts market is considered part of the over-the-counter (OTC) markets. Transactions in these markets are conducted directly between parties or through brokers, electronic platforms, financial institutions, etc. The terms in these contracts, including prices, are determined based on the risk boundaries and strategies of the buyer and seller. The lack of transparency regarding prices agreed upon in bilateral contracts can negatively impact market competition. Sellers can offer different prices to different buyers, and since these contracts are made well before physical delivery, price discrepancies between contract and market conditions at the time of delivery can result in reduced profits or even losses for sellers, potentially leading to market withdrawal and contract termination, adversely affecting competition [10].

Launched in 2021 and operated under EPİAŞ, the futures electricity market allows market participants to conduct forward physical electricity delivery and hedge against significant future price fluctuations. The market facilitates predictions of future electricity unit prices. Market transactions are carried out by buying and selling contracts related to load types, delivery periods, and bid regions determined by the market operator. Participants submit buy-sell bids for specific contracts, and trades are executed based on matching these bids. Unlike bilateral contracts, trades in the futures electricity market are standardized and conducted under EPİAŞ, eliminating counterparty risk [10].

1.3.3 Real-Time Markets

Real-time markets, operated by TEİAŞ, include the balancing power market and ancillary services market. The primary goal of these markets is to maintain market balance rather than facilitate electricity trading. Despite the balancing roles of DAM and IDM, unforeseen events can disrupt the supply-demand balance in real time, necessitating the involvement of real-time markets. Participants initially trading in the bilateral contracts market and subsequently in the DAM and IDM if balance is not achieved ultimately participate in real-time markets to ensure balance.

Under real-time markets, the balancing power market aims to provide real-time balancing services to the system operator by supplying reserve capacity within a maximum of 15 minutes. Meanwhile, the ancillary services market ensures frequency and demand control [10].

1.3.4 Spot Markets

Spot electricity markets, like financial markets, operate on the principle of matching trade offers, but they differ in the time between setting trade terms (price, quantity, time frame) and the actual physical delivery. Due to the structure of the supply chain, physical delivery occurs according to a planned schedule based on forecasts. Additionally, the instantaneous load at all distribution points within the system is balanced through various markets that allow for the use of an increasingly comprehensive set of information as the delivery time approaches. Correspondingly, the level of risk also increases according to the market participants' risk desire. The characteristics of this market will be detailed in the next section.

1.3.4.1 Balancing Power Market

In markets where physical delivery of electricity takes place, unexpected plant outages or sudden spikes in demand can upset the system's balance. In such scenarios, TEİAŞ, the operator of the balancing power market, utilizes previously submitted bids to restore equilibrium. Reserves are maintained on standby to manage these imbalances, ensuring the system operates continuously and stably [10].

Frequency control is essential in the balancing power market. The standard grid frequency is 50 Hz. A frequency below 50 Hz signals that consumption exceeds production, requiring either a decrease in consumption or an increase in production to reestablish balance. Conversely, a frequency above 50 Hz indicates that production surpasses consumption, necessitating a reduction in production. The goal of the balancing power market is to keep the frequency as close to 50 Hz as possible.

Balancing units, which can adjust production by at least 10 MW within 15 minutes, are mandated to participate in the balancing power market. These units must submit bids for both increasing and decreasing load, which are assessed daily by the market operator. The System Marginal Price (SMP) is a crucial concept in this market, defined as the bid price corresponding to the net instruction volume during periods of energy surplus or shortage.

1.3.4.2 Ancillary Services Market

Under TEİAŞ, the ancillary services market ensures both the secure operation of the transmission and/or distribution system and the provision of high-quality electricity services. This market includes frequency control, voltage control, and reactive power support [10].

The ancillary services market encompasses reactive power support, primary frequency control, and secondary frequency control. In primary frequency control, the active output of the production unit is automatically adjusted. In secondary frequency control, the central system adjusts the active output to a set value. Reactive power support helps balance reactive power when needed in the system [12].

1.4 Spot Electricity Markets

In Turkey, the spot electricity market, used for buying, selling, and balancing electricity, is operated by the Energy Exchange Istanbul (EXIST). This market operates through two main platforms: DAM and IDM [13].

1.4.1 Day-Ahead Market

The DAM is managed by the Energy Markets Operator (EPİAŞ). It facilitates the trading of electricity for physical delivery on the next day. This market helps balance supply and demand to prevent disruptions in market activities. Participation in the DAM is not mandatory. Market participants submit bids with varying quantities and prices for each hour, which are processed to balance portfolios. Transactions are conducted daily and hourly, establishing prices a day before delivery. The DAM helps protect participants from potential imbalances and real-time market price risks [14].

The DAM provides a mechanism where energy buyers, sellers, and other participants can engage in trade without mandatory involvement. It offers opportunities to balance portfolios and establish a reference price for electricity. Participants who do not join the DAM can manage their balance through bilateral agreements or by trading in the IDM.

Participants aim to buy at low prices and sell at high prices. There are three types of bids: hourly, block, and flexible. The DAM operates with daily transactions over 24-hour periods, allowing adjustments in supply and demand quantities based on price levels. The reference price, known as the market clearing price (MCP), is determined daily. Offers and bids are submitted from five days before (D-5) to one day before (D-1) the delivery day, with a final submission time of 12:30 PM (D-1). Confirmations and optimizations are done by EPİAŞ between 12:30 PM and 1:30 PM, with results announced by 1:30 PM. Participants can object to transaction confirmations by 1:50 PM, and final prices and volumes are published at 2:00 PM.

Participants can submit bilateral agreement notifications daily between 00:00 and 17:00, with validations conducted between 17:00 and 17:05. Appeals regarding canceled contracts can be made between 17:05 and 17:15.

1.4.2 Intraday Market

The IDM allows trading up to one hour before physical delivery, helping maintain market balance. Managed by EPİAŞ since 2015, this market supports balancing portfolios in near real-time and accommodates RESs. Participation in the IDM is voluntary [10].

Participants can use the IDM to mitigate unforeseen imbalances that might arise after DAM transactions. Electricity purchased but not used in the DAM can be sold in the IDM, enhancing market volume and price stability. IDM transactions occur hourly from midnight to the following midnight. Orders can be updated until one hour before delivery. The market is open for order submission daily from 6:00 PM until the market closes.

IDM facilitates physical energy trading up to an hour before delivery and reduces energy imbalances. It employs continuous bilateral trading, prioritizing the highest buy and lowest sell prices. If prices match, earlier orders are prioritized [10]. There are two types of IDM bids: hourly and block bids. Hourly bids are divisible and cover 24 hours. Block bids are indivisible, covering 1 to 24 hours within the same day.

1.5 Pricing Methodologies in Electricity Markets

Pricing methodologies in electricity markets are essential for the efficient distribution of power generation and the stability of the system. Pricing methods establish the prices for electricity by taking into account generation, transmission, and distribution costs, as well as the physical limitations of the power grid. Among these methods are uniform pricing, which applies a single price across the entire market, and more detailed approaches like nodal and zonal pricing, which consider locational variances and grid constraints. Each method impacts market dynamics, investment strategies, and system efficiency in distinct ways.

1.5.1 Locational Price Methods

The aim of a deregulated electricity market is to achieve both short-term and long-term efficiency. This involves the efficient utilization of current resources in the short term and the optimal development of the power system in the long term. Efficient short-term usage of generation and transmission capacities can be determined by solving an Optimal Economic Dispatch (ED) problem, where the goal is to maximize the difference between consumer benefits and production costs while adhering to generation and transmission constraints, including security limits. Solving this problem yields a value of electricity for each location within the transmission network, which serves as a benchmark for evaluating congestion management methods.

1.5.1.1 Marginal Pricing

The marginal pricing method, often referred to as the 'pay-as-clear' market, underpins the EU electricity market, particularly in day-ahead auctions and balancing energy markets. This approach ensures that all market participants receive the same wholesale price for electricity, which is set by the marginal cost. Producers are sorted in merit order, starting with the least costly options and moving to more expensive ones. The final plant needed to meet the demand determines the clearing price, and all producers whose bids are below this price receive the same payment [15].

This system incentivizes all electricity producers to bid their actual costs to secure a place in the merit order and be dispatched. This is in contrast to speculative bidding, as producers aim to be dispatched as much as possible and are compensated uniformly if their bids fall below the clearing price.

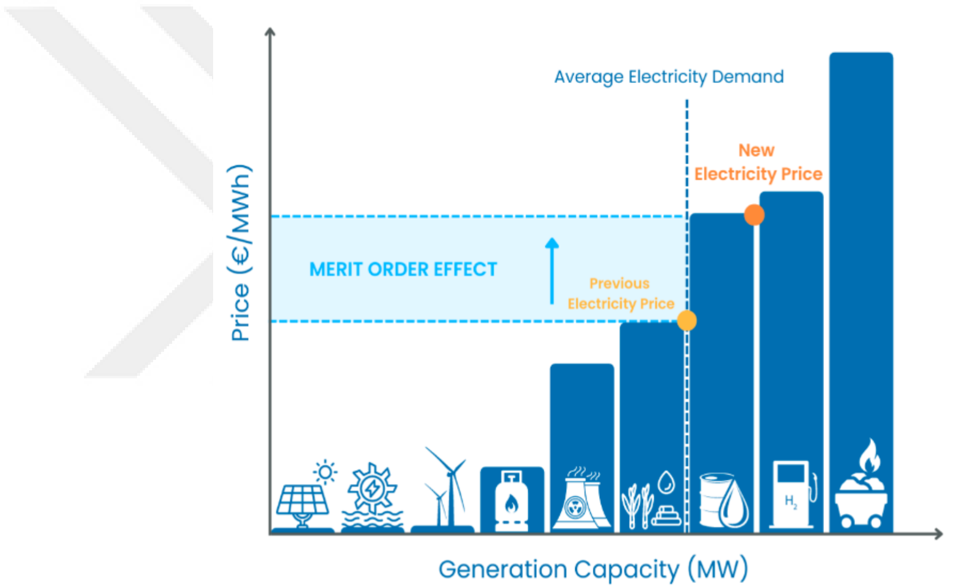

Figure 7: An illustration of Merit Order Curve [16].

The merit order is the order in which electricity-producing units are activated to supply power based on their increasing variable or marginal production costs, as seen in Figure 7. Fossil-fuel power plants usually have high marginal costs due to the fluctuating prices of underlying commodities like coal, gas, and oil. These fluctuations can alter the relative positions of these units in the merit order over time. Renewable and nuclear units, with low operational costs per MWh, are typically at the beginning of the merit order, as they need to generate electricity before the more expensive units.

The marginal price is determined at the point where the supply and demand curves meet, representing the revenue earned by all production units for their sold volume and the cost paid by all market participants for electricity. This unique price per bidding zone encapsulates all available information about supply, demand, and transmission capacity. This 'pay-as-clear' mechanism contrasts with the 'pay-as-bid' mechanism, where each generation unit is paid based on its declared cost rather than the marginal cost of the last unit needed to meet demand [17].

1.5.1.2 Nodal Pricing

Nodal prices, which are detailed in [18], refer to location-specific prices set according to the principle of aligning prices with marginal costs in electricity markets. These prices are designed to optimize overall social welfare while accounting for the physical constraints of the transmission network and, where applicable, transmission losses. [19] proposed the idea of contract networks to offer financial capacity rights, and [20] introduced heuristics for managing contingencies.

The physical laws governing electricity flow and its tendency to use all available paths between source and destination result in unique characteristics for nodal or locational marginal prices (LMPs). Constraints in the network can lead to varying prices at different locations, and power can sometimes move from a node with higher prices to one with lower prices. Furthermore, introducing a new transmission line might decrease the overall social surplus. In a network in Figure 8 that includes all points of electricity injection and withdrawal, as well as all node connections, the nodal pricing mechanism will determine a price for each connection point in the system [21].

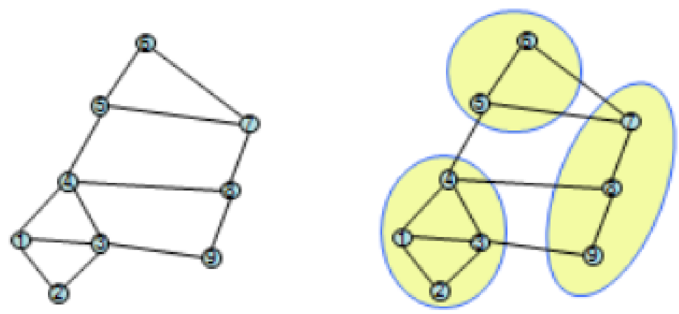

Figure 8: An illustration of Nodal and Zonal Pricing [21].

1.5.1.3 Zonal Pricing

Zonal prices serve as a simplified version of nodal prices, resulting in fewer price points by aggregating some elements. The exact method of aggregation is not well defined and can involve either just the prices or the physical network model itself, as illustrated by the section of Figure 8.

When only prices are combined, known as economic aggregation, the overall network structure remains intact, but prices are kept the same within certain zones. This is shown in the right part of Figure 8, where nine nodes are grouped into three zones while the original network remains visible. Here, bids are made for individual nodes, and capacities are specified for each line, but prices are determined for the zones. These prices are termed optimal zonal prices because they are derived by solving an optimal economic power flow problem, with the additional requirement that prices within the same zone must be equal. Optimal zonal prices, as studied in [22], are considered the second-best alternative to optimal nodal prices.

Different zone divisions may benefit different market participants, such as producers and consumers, who often have opposing interests. Furthermore, grid revenues could become negative with optimal zonal prices, and adverse power flows, where power moves from higher-priced to lower-priced zones, can occur frequently. Finding an optimal zone division is challenging due to varying market characteristics, hourly costs, and network topology, making it difficult to establish a fixed zone division over a long period. If zones are too few, maintaining uniform prices within predefined areas while satisfying all constraints may be impossible [21]. In the Simplified Zonal Pricing approach, the detailed network is replaced with aggregated nodes and connections, making the network simpler and ignoring the specific details of power flows. However, this simplification is challenging for electricity networks because injections and withdrawals at different nodes within a zone can have very different effects on the system. It's also complicated to determine the properties of aggregated lines, such as their admittance and capacity.

CHAPTER II

ELECTRIC VEHICLES

In this chapter, a comprehensive understanding of EV technology, the various types of EVs, the infrastructure supporting EV charging stations (EVCSs), the integration of EVs into the electricity network, and the broader implications of EV charging on the electrical grid will be provided.

2.1 Electric Vehicle Technology

The first EV model, as shown in Figure 9, was designed by Professor Stratingh in 1835 and was first implemented by Thomas Davenport. In the first EV model, there were non-rechargeable batteries discovered by Robert Anderson in 1832 [23]. Lead-acid batteries were discovered by Gaston Planté. This led to the use of rechargeable lead-acid batteries in EVs. In 1882, Prof. William Ayrton and John Perry designed a three-wheeled vehicle that could reach 14 km per hour, using a ten-fold lead acid battery in each wheel. The EV, designed in 1882, was the fastest vehicle in EV design up to that time [24].

Figure 9: The First Electric Car [25].

As electrical infrastructure systems advanced, the idea of developing electric vehicles (EVs) continued to evolve alongside traditional internal combustion engine vehicles, leading many countries to begin producing both types of vehicles [23]. The first commercial production vehicle was the Electric Carriage and Wagon Company's Electrobas in 1897. The idea of improving range and performance laid the foundation for hybrid vehicles. French Electroautomobile in 1900 and Krieger in 1903 developed both electric and gasoline vehicles.

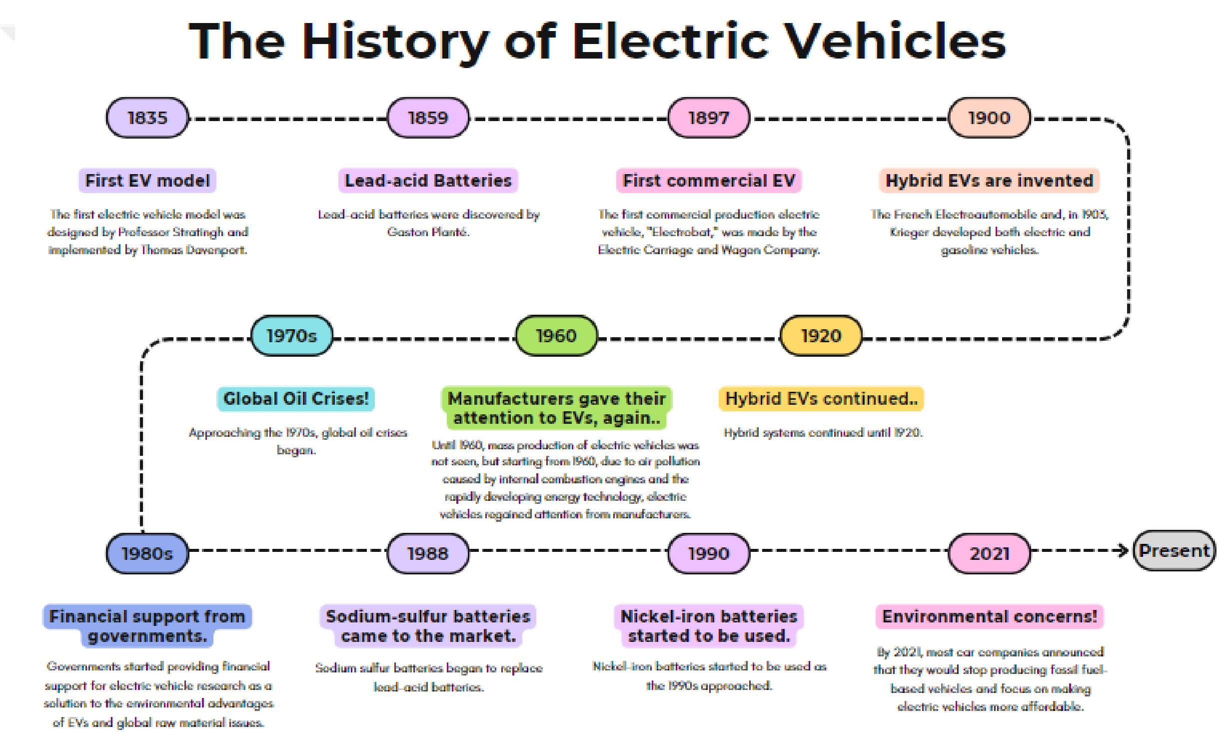

Figure 10: History of Electric Vehicle Developments.

EVs, not seen in mass production until 1960, regained the interest of manufacturers from 1960 onwards due to the air pollution caused by internal combustion engines and the rapidly developing energy technology. Many prototypes were produced. As the 1970s approached and global oil crises began, manufacturers increasingly turned to EVs. They focused on strengthening EV features and achieving high-range, high-performance operations by contributing to advancing technology. In the 1980s, governments began funding research into EVs to address their environmental benefits and global raw material challenges. Power electronics systems began to gain more prominence. In 1988, sodium-sulfur batteries began to replace lead-acid batteries. Research began on AC drives alongside DC drives. Almost all manufacturing countries and companies have started contributing to EV production. As the 1990s approached, nickel-iron batteries started being used [24]. From the 1990s onwards, the rapid advancement of technology, continuous market and industry growth, and the spread of computer technology led to continuous development in EVs.

By 2021, most car companies announced that they would stop producing fossil fuel-based vehicles and that their primary goal is to work on making EVs more affordable. The history of the development of EVs is summarized in Figure 10. Many battery studies have been conducted. Currently, lithium-ion-based batteries are powering EVs, which are quickly surpassing internal combustion engine vehicles in performance, range, environmental impact, and technical safety [23]. A comparison with traditional cars, often cited as the main competitor in EV development, is presented in Table 4.

Table 3: Comparison table between traditional cars and electric vehicles.

Aspect	Traditional Cars	Electric Vehicles
Advantages	Short fuel refueling times and no range issues.	Simpler motor design and shorter production-assembly times.
	Lower initial purchase costs.	More reliable due to the use of alternative energy.
	Sufficient number and frequency of fuel stations.	Higher efficiency.
		More environmentally friendly.
		Simpler motor components requiring minimal maintenance except for the battery.
		Lower unit cost of consumed energy.
Disadvantages	Complex motor designs leading to insufficient efficiency despite using high-energy fuel.	Long battery charging times and insufficient battery capacities.
	Noisy operation due to energy transformations in the combustion chamber.	High battery replacement costs during periodic maintenance.
	Emission of harmful gases contributing to greenhouse effect and global warming.	High initial purchase prices despite various incentives compared to traditional vehicles.
	High and frequent maintenance costs due to complex motor designs and numerous components	Limited number of electric vehicle charging stations, long charging times, insufficient battery capacities.
	Reliance on depleting fossil fuels, causing environmental and economic issues.	Current battery technology not providing sufficient energy, leading to range problems
	Dependence on imported oil, posing a significant economic disadvantage.	

2.2 *Types of Electric Vehicles*

The landscape of EVs is diverse, encompassing several distinct categories that provide to varying needs and technological advancements. Each type of EV employs different mechanisms to harness electric power, offering unique benefits and challenges.

2.2.1 Battery Electric Vehicles (BEV)

Battery Electric Vehicles (BEVs), as illustrated in Figure 11, do not feature an internal combustion engine, unlike conventional vehicles. BEVs are simpler in design, having fewer components compared to vehicles that use fossil fuels. They are powered by an electric motor driven by a battery, eliminating the need for a fuel tank.

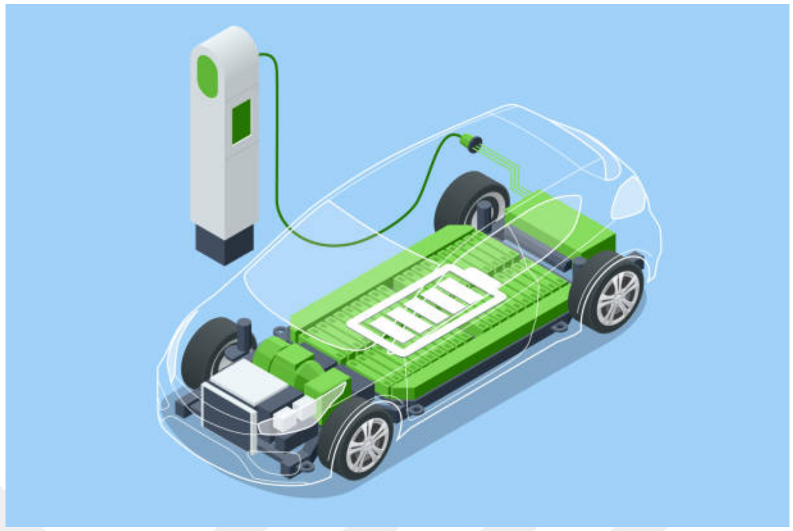

Figure 11: Battery Electric Vehicle Working Scheme [26].

Many BEVs are powered by rechargeable lithium-ion batteries, which are compact and have very high energy density. To charge BEVs, it is first necessary to connect them to a charging station [27]. The charging station converts AC electricity from the grid into DC power to charge the main battery. In this way, the vehicle begins to charge, and electrical energy is stored in the batteries. When the gas is pressed to start the vehicle, the power is directed from the battery to the electric traction motor, which provides the vehicle with the energy required for movement.

BEVs offer the advantage of low fuel costs since they run entirely on electricity, and their maintenance costs are also lower compared to other EVs. However, BEVs face drawbacks such as range concerns due to their limited battery capacity, with an average range of 100-300 km, leading to the need for frequent charging. Additionally, charging times are long, and the infrastructure required for fast charging solutions is expensive.

2.2.2 Hybrid Electric Vehicles (HEV)

Nowadays, HEVs, shown in Figure 12, are gaining popularity due to the growing urban population and the rising number of vehicles. These vehicles use a gasoline engine for regular driving but switch to an electric motor during heavy traffic and challenging conditions, which helps save energy [28]. Apart from its internal combustion gasoline engine, the vehicle also includes a battery, a generator, and an electrically powered engine.

While the vehicle operates with a gasoline engine during its normal progress in traffic to consume less gasoline during stops and stalling, the electric motor is changed automatically, not by the driver. In these vehicles, there is never a decrease in efficiency due to the use of alternating engines. Basically, HEVs have the logic of achieving the highest performance with the highest efficiency.

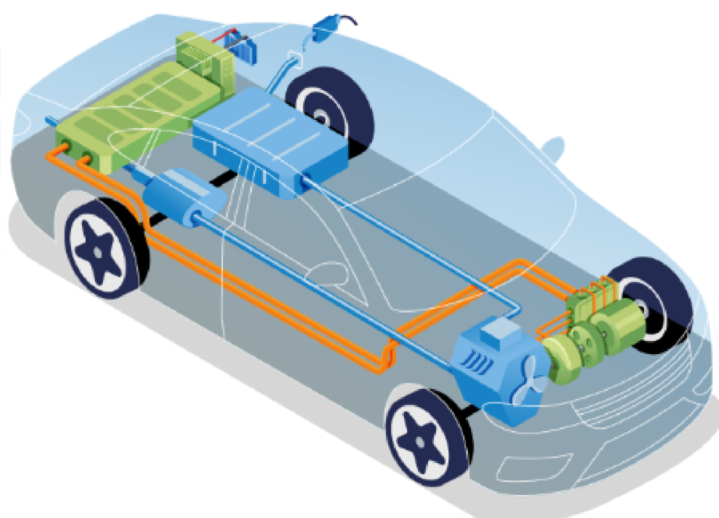

Figure 12: Hybrid Electric Vehicle Working Scheme [29].

HEVs offer the advantage of saving fossil fuels by using the electric motor up to a certain speed limit. They efficiently transfer energy to the batteries through regenerative braking and are highly economical for urban use where high speeds are unnecessary. However, HEVs also have disadvantages, including increased maintenance frequency and costs due to the combination of the internal combustion engine and batteries. Additionally, they may not provide sufficient performance and efficiency at higher speeds.

2.2.3 Plug-In Hybrid Electric Vehicles (PHEV)

PHEVs, shown in Figure 13, are an excellent option for users interested in transitioning to electric vehicles but hesitant about committing to a fully electric model. These vehicles can run on diesel or gasoline when a charging station is unavailable or the vehicle cannot be charged for any reason [30]. The engine operation of PHEVs is similar to that of self-charging hybrid vehicles. However, PHEVs feature larger batteries than traditional hybrids, allowing them to be charged by plugging into a charging unit.

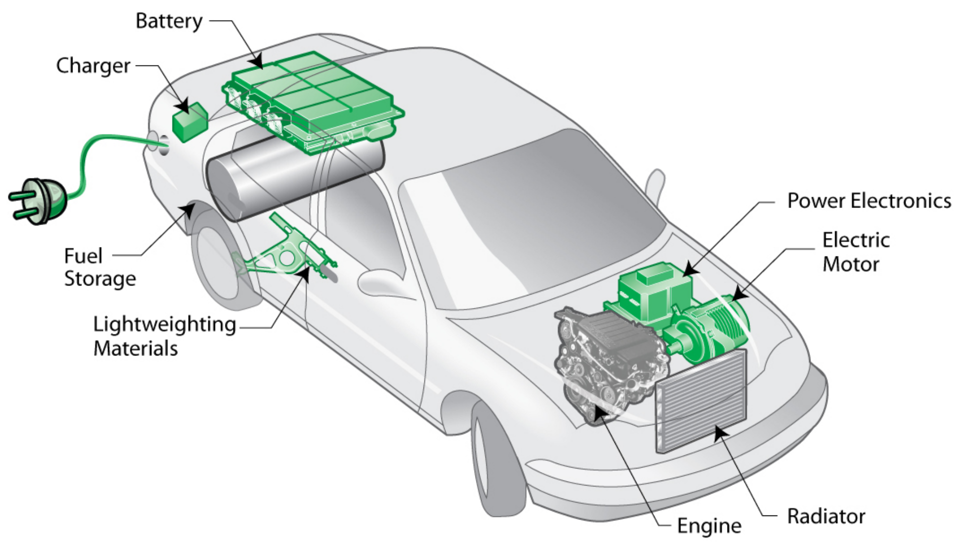

Figure 13: Plug-In Hybrid Electric Vehicle Working Scheme [31].

PHEVs are typically used in fully electric mode, and the vehicle runs on electricity until the charge is completely exhausted. When the battery is discharged, the internal combustion engine takes over. In this way, while the vehicle operates like a traditional hybrid, it provides a functional use in that it can also supply power by charging.

PHEVs offer several advantages, such as eliminating range issues by combining a traditional internal combustion engine with rechargeable batteries. They provide significant savings because the electric motor is designed as the main engine, and their limited battery capacity allows for short charging times. Additionally, PHEVs can transfer mechanical energy directly to the batteries using regenerative braking. However, they also have disadvantages, including the limited use of the electric motor due to the restricted battery capacity and high maintenance costs because of the need to maintain both the internal combustion engine and the batteries.

2.3 EV Charging Stations (EVCSs)

The successful adoption of EVs depends greatly on the presence of EVCSs. These stations are vital as they provide the necessary infrastructure for consistent and dependable charging of EVs. They play a key role in addressing the energy needs of EVs, enabling safe and effective charging, and ensuring smooth integration into the power grid. Understanding the significance and operation of EVCSs is fundamental to overcoming the challenges associated with the rising number of EVs and supporting their incorporation into the current energy systems.

2.3.1 Hardware of chargers

A power unit is responsible for supplying and regulating the DC needed to charge a battery from an electrical energy source. Batteries typically require a DC voltage range of 200-500V for charging. Since most current electrical energy sources provide AC, this unit usually includes an AC/DC converter. However, modern advanced battery chargers can deliver charging power directly from a DC source. This unit must be designed to effectively meet the battery's charging requirements while ensuring efficient and high-quality electrical energy. Depending on the design, this unit can be located either on the vehicle or externally.

To optimize battery charging, a charger requires information such as the battery's charge status, temperature, voltage, and current. This is managed by the Battery Energy Management System (BEMS), which consists of a microprocessor and sensors positioned near the battery within the vehicle. The microprocessor runs the battery's charging algorithm while the sensors monitor the battery's voltage, current, and temperature. Based on the sensor data, the microprocessor adjusts the charging current accordingly. The BEMS also safeguards against any internal or external battery issues that may arise during charging. In case of an error, the system will identify the issue and stop charging if necessary.

2.3.2 Charging methods

New and creative solutions are emerging to enable EVs to become widely adopted. A key aspect of this progress is advancements in charging technology. Charging technologies generally used for battery charging in the literature are given in Figure 14 [32]. The first and most common technology is the conductive charging type. In this type of charging, the battery is charged directly using an external cable. Both AC and DC charging solutions are available in conductive charging.

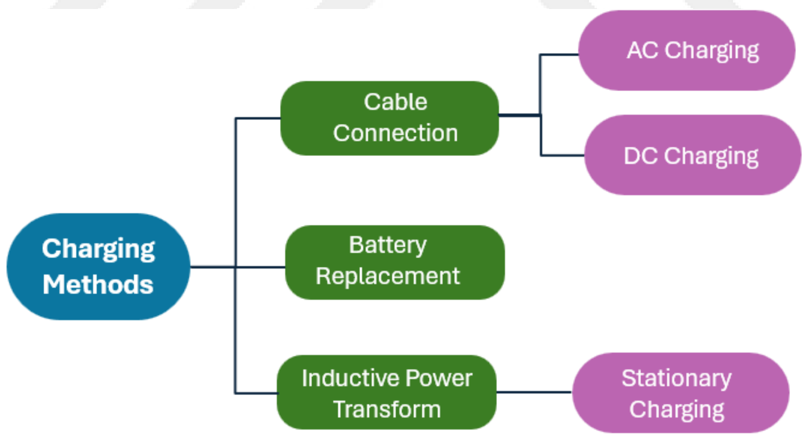

Figure 14: Charging methods of EVs.

2.3.2.1 Cable Connection

Wired charging involves the driver connecting the vehicle to a charging station with a cable. This approach provides high efficiency and reliability, ensuring a robust link between the car and the charging station. There are two types of wired charging: on-board (internal) and off-board (external).

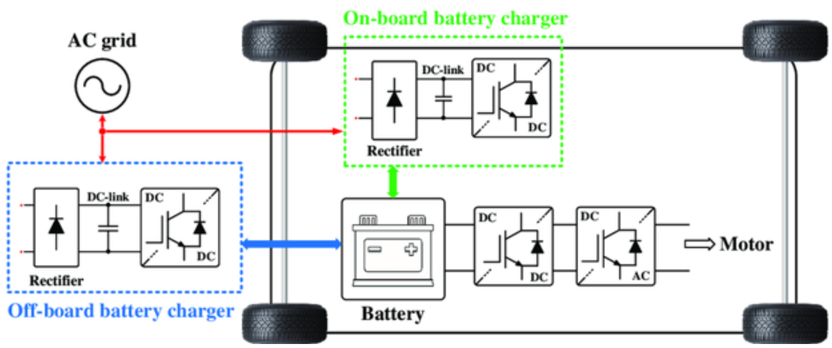

Figure 15: Wired EV Charging system with on-board and off-board [33].

As seen in Figure 15, in the internal charging method, the rectification circuit is located on the vehicle, while in the external charging method, it is located on the charging station. External charging stations charge the vehicle with DC.

2.3.2.2 Inductive Power Transform

Inductive charging, as shown in Figure 16, is a form of wireless charging that stands out as a practical alternative for EV users following wired charging methods. Unlike wired charging, inductive charging offers convenience without physical connections. It can be categorized into static and dynamic charging [34]. However, this technology is too expensive and inefficient to be commercialized for today's technology.

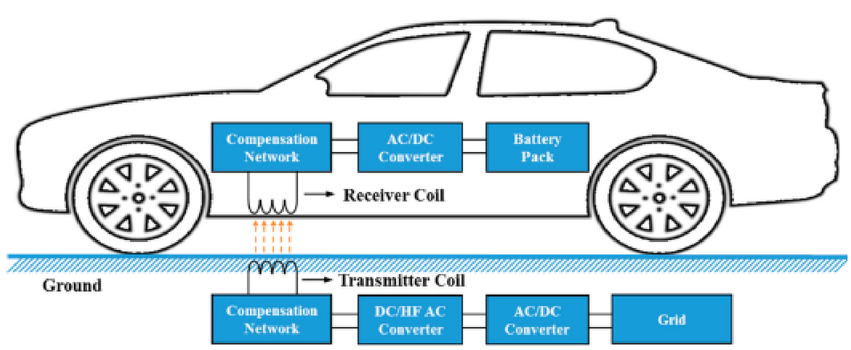

Figure 16: Structure of the inductive power transfer system for EV charging [33].

2.3.2.3 Battery Replacement

The method depicted in Figure 17, known as 'Battery Exchange,' has been developed to considerably reduce the time required for charging electric vehicles. This approach entails paying a monthly subscription fee for battery access. At battery swapping stations, a slow charging method is used, which helps extend the battery's life. The process involves taking out the depleted battery and replacing it with a fully charged one.

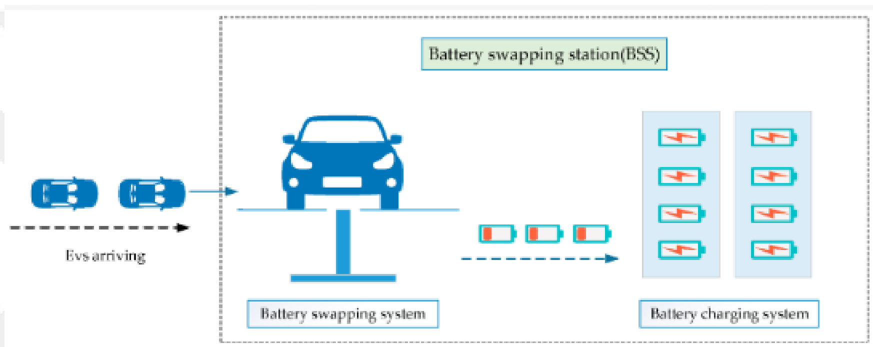

Figure 17: EV battery swapping technology [35].

This method requires visiting a battery swapping facility, where an automated system positions the car, removes the old battery, and installs a fully charged one. The drained batteries are recharged at these stations for future use. Although the battery-swapping method appears to be very convenient, significant investment is required to build battery-swapping stations distributed across cities.

2.3.3 EV charging power classes and capacities

To fully understand the implications of EV charging and the infrastructure of EVCSs, it is essential to analyze various factors such as their impact on the network, associated costs, site selection, charging times, and power needs [36].

The time required to charge an EV is influenced by elements like EV's battery capacity and the power capacity of the charging station. Future technological advancements are expected to reduce these charging times significantly.In fact, these values are decreasing rapidly today. For example, Jean De La Verpilliere, CEO of Echion Technologies, says that these batteries produced with niobium anode can be charged in 6 minutes [37].

There are 3 types of charging points on the market [38]:

1. Normal power charging point: It is the charging point that transmits 22 kW and below power to the EV.

2. High power charging point: A charging point that transmits more than 22 kW of power to the EV. Although 50 kW charging points are common, such charging points are developing rapidly, and today, there are 175 kW and above charging points.

3. Load balancing/charging plaza: This type of charging point has many charging points connected to the grid from a single location. The charging plaza enables EV drivers to charge their vehicles optimally, ensuring that the appropriate capacity is delivered to the charging points according to demand within a certain period of time. This is also called load balancing. The charging speed is automatically adjusted when the highest capacity is reached.

2.3.4 EV charging modes

The International Electrotechnical Commission (IEC) standard 61851-1 outlines four charging modes for EVs based on the type of power received, voltage level, presence of two-way communication between the vehicle and charging station, and the inclusion of grounding and protection devices [39].

Charging modes are classified as follows:

1. AC Mode 1: In AC Mode 1, one end of the cable connects to the vehicle's charging port, while the other end plugs into a standard household wall socket. This mode lacks built-in protection against electric shock, relying only on the home's existing safety installations.

2. AC Mode 2: AC Mode 2 charging also uses a standard socket but incorporates an external vehicle supply equipment cable, often provided by the EV manufacturer. This special cable includes residual current device protection, maximum current protection, and increased temperature protection.

3. AC Mode 3: AC Mode 3 allows for faster charging compared to Modes 1 and 2, depending on the grid connection and the vehicle charger's power. Additionally, it establishes communication between the vehicle and the socket through a pilot line.

4. DC Mode 4: DC Mode 4 employs an off-board charger with AC to DC converters. This mode can recharge the vehicle in under an hour with a DC power supply. The vehicle communicates with the external charger to ensure full charge control and protection against electric shocks.

All charging modes are illustrated in Figure 18 below.

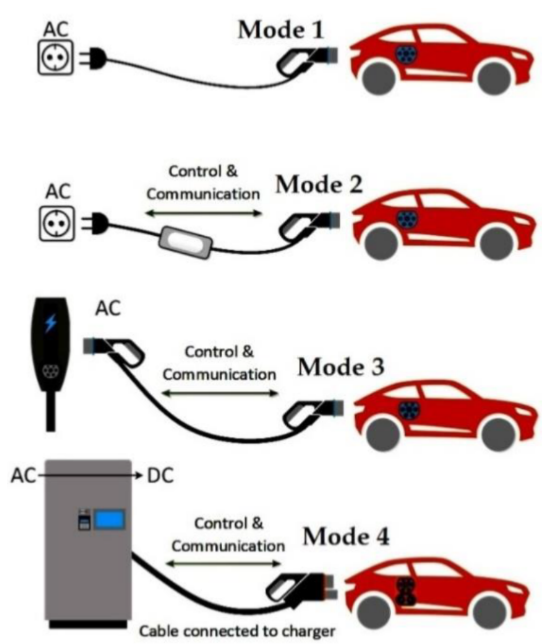

Figure 18: EV charging modes according to IEC 61851-1 [39].

2.3.5 Locations of EV Charging Stations

One of the most significant drawbacks for EV owners or potential EV buyers is the availability of charging stations. There are four main locations where vehicle owners can charge their EVs.

1. Residential Charging Stations: This type of charging is installed at users' homes and generally uses AC-level charging. During the night hours, when demand is relatively lower, EV owners can charge their vehicles at home until the morning.

2. Workplace Charging Stations: Drivers who go to work with their electric cars can charge their vehicles at their workplaces during hours when the electricity demand from the grid is less.

3. Fleet Charging Stations: Most companies install charging stations for EVs in their fleets.

4. Commercial Charging Stations: Commercial charging stations include charging units with different charge levels. Installing those in places like shopping malls, theaters, and restaurants helps alleviate potential EV buyers' concerns about charging.

The number of EV charging stations is increasing due to the peak in EV market in Turkey as well as in the world. EV charging stations in Turkey are shown in Figure 19.

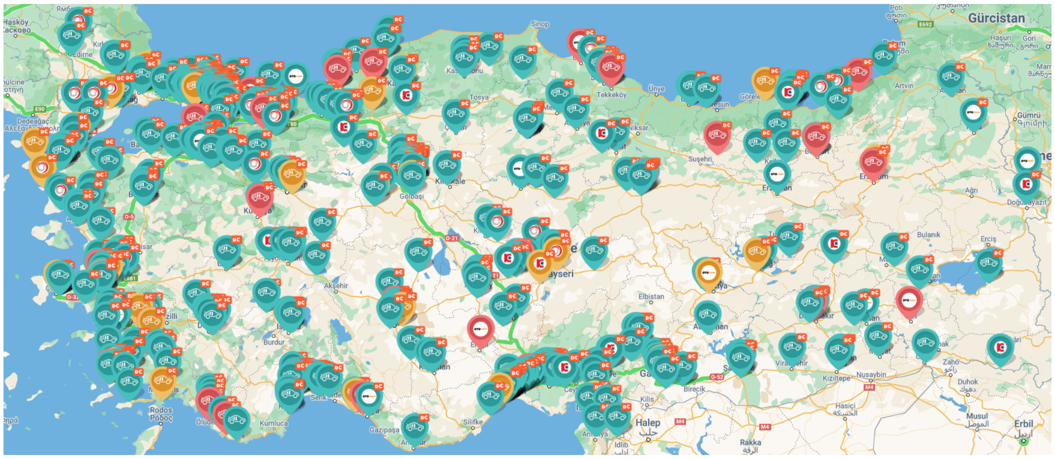

Figure 19: Map of charging stations installed in Turkey [40].

2.4 Integration of EVs to the Electricity Network

EVs need a filling facility and need to be charged, just like fossil fuel vehicles. EV batteries are charged/discharged using DC. However, AC is generally used mostly in charging stations and homes. For this reason, to charge the EV, we need to convert the AC power coming to the charger into DC power and, during discharge, convert the DC power into AC power. These conversions are made through an inverter [41].

Electric and hybrid vehicles store electrical energy in their batteries by transferring power from the network. Batteries on EVs use an AC/DC converter for the supply coming from the network, and then the voltage values are reduced to the appropriate level with DC/DC converters, and the electrical power is optimally stored on the battery. This method provides a one-way transfer from the grid to the batteries.

In addition to being a load fed from the electric grid, if EVs are designed to be integrated into power systems, they can be used as dynamic energy storage systems that feed the grid. Bi-directional EV chargers are systems that enable EVs to exchange power bi-directionally to the grid [42]. This bi-directional power flow is shown in Figure 20.

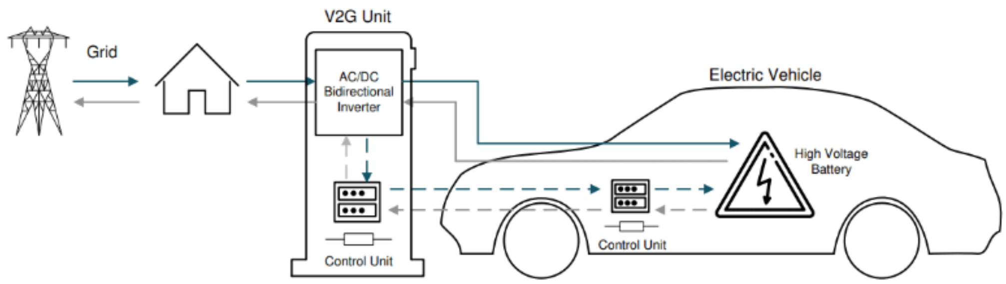

Figure 20: Bidirectional smart grid representation [43].

Disruptive effects such as short- and long-term load changes, voltage fluctuations, frequency changes, sinusoidal distortions, and noise can reduce power quality [42]. If these situations are not detected in time and precautions are not taken, they reduce the power quality and cause significant losses for both suppliers and consumers.

EVs are swiftly gaining popularity as a primary mode of transportation due to their elimination of reliance on fossil fuels. For this trend to continue growing and becoming more widespread, it is essential to develop more efficient and faster EVCSs. Due to the low efficiency of charging and significantly longer charging times compared to fossil fuel vehicles, EVs are often limited to urban or short intercity transportation levels. Designing fast EVCSs correctly is crucial for both drivers and manufacturers. The goal of fast EVCSs is to reduce charging times, thereby saving time and efficiently charging the EV's battery in a shorter period [44].

2.5 Potential Growth of EVs and EVCSs in Turkey

A rapid expansion in the EV ecosystem is currently being observed, with electric vehicles becoming more prevalent in daily life. Increasing the number of EVs in the country and rapidly expanding the EVC Charging (EVC) infrastructure nationwide have been identified as strategic objectives. The EVC network infrastructure is considered crucial for achieving energy efficiency and carbon footprint reduction goals, as it forms the foundation of an environmentally friendly transportation system. The country's renewable energy potential and advanced energy infrastructure are recognized as significant opportunities to support the widespread adoption of EVs.

In this context, Turkey's EVC infrastructure is being developed through incentive policies implemented by public institutions and organizations, as well as private sector participation. Support mechanisms are being explored for the installation and widespread deployment of charging stations in urban and rural areas, aiming to provide adequate infrastructure for EV to meet their charging needs conveniently. Additionally, the utilization of RESs is being encouraged to promote using more environmentally friendly and sustainable energy sources for charging EVs. Furthermore, various efforts are being undertaken to develop and widely implement energy storage technologies.

At the beginning of 2023, 14,896 EVs were present in Turkey, while this number has reached 93,973 as of today. As a result of investments made by charging network operators licensed by the Energy Market Regulatory Authority (EMRA), the number of charging points (sockets), which stood at 3,081 (2,706 AC (Slow) and 375 DC (Fast)) at the beginning of 2023, has increased to 17,233 (11,412 AC (Slow) and 5,821 DC (Fast)) as of April 1, 2024. The rapid increase in both EVs and EVC points is considered a positive development for the growth of the e-mobility ecosystem. In the country, the ratio of EVs per socket is 5.4, compared to the European average of 13.75, indicating a favorable position [45].

Table 4: Projections of Electric Vehicle's Number.

	Number of Electric Vehicles		
Year	**Slow-Rise Scenario**	**Medium-Rise Scenario**	**High-Rise Scenario**
2025	202.030	269.154	361.893
2030	776.362	1.132.932	1.679.600
2035	1.779.488	3.307.577	4.124.273

Table 5: Projections of EV Charging Point's Number.

	Number of AC Charging Point			Number of DC Charging Point		
Year	**Slow-Rise Scenario**	**Medium-Rise Scenario**	**High-Rise Scenario**	**Slow-Rise Scenario**	**Medium-Rise Scenario**	**High-Rise Scenario**
2025	24.983	33.476	44.988	9.295	12.594	16.909
2030	58.717	100.187	127.224	24.826	42.637	54.050
2035	100.150	186.152	237.181	46.766	86.924	110.753

According to projections in Table 5 and 6, the total electricity consumption attributed to EVs is estimated to range between 1.69 TWh and 3.56 TWh in 2030, and between 3.98 TWh and 9.39 TWh in 2035. The Turkey National Energy Plan forecasts electricity consumption to reach 455.3 TWh in 2030 and 510.5 TWh in 2035. Even in the highest projection scenario, the electricity consumption from EVs is expected to account for less than 1% of total electricity consumption in 2030 and less than 2% in 2035 [45].

Considering the ongoing expansion of Turkey's electricity distribution network, new investments, and low transformer capacity utilization rates, it is assessed that there will be no significant additional investment requirement for charging stations in Turkey's electricity distribution network in the near future, taking into account projected electricity consumption from EVCSs.

CHAPTER III

DISTRIBUTION LOCATIONAL MARGINAL PRICING

In this chapter, the key concepts and methodologies crucial to electric power systems are explored. Subtitles for this chapter cover Optimization, Linear Programming (LP), Optimal Power Flow (OPF), Locational Marginal Pricing (LMP), and Distribution Locational Marginal Pricing (DLMP). These topics provide a comprehensive understanding of optimization techniques and economic principles in modern power systems.

3.1 Optimization

Optimization is the process of solving an existing problem by placing it in the created system to best minimize or maximize it with the resources available in the system. In the process of finding the best solution, it is necessary to choose one of the alternative solutions set to the problem under certain constraints. The steps of optimization before solving are to determine the mathematical terms of the objective function, variables and constraints of the problem.

Optimization, mathematically defined, can be encountered in all areas of life. Therefore, the ability to mathematically express the problem encountered is the most crucial component of optimization, while the step of solving to find the best solution set that satisfies the expressed model is another critical component.

Models are structures of smaller scale that reflect all the features of a large-scale system, extensively used in the natural sciences and engineering. Optimization models consist of mathematical expressions that reflect the operation and characteristics of the system and encompass its connections with other systems within and around it [46]. The general terms used in optimization are provided in Equation 3.1.

$$
\begin{aligned}
& \min f(x) \\
\text{subject to:} & \\
& g(x,u) = 0, \\
& h(x,u) \leq 0
\end{aligned}
\tag{3.1}
$$

The objective function $f(x)$ given in Equation (3.1) is a quantitative measure of the system's performance, representing the best solution to be achieved through minimization or maximization in optimization [46]. In a power system, the targets that can be achieved include minimizing technical losses, minimizing system costs, maximizing social welfare, etc.

The variables expressed as x are the components of the system created to reach the objective function. In power systems, variables can include the number of electric vehicles that can be connected to the grid, power generators' outputs, the system's generation capacity, or the location of the power plant, among others.

The constraints $g(x,u) = 0, h(x,u) \leq 0$ are functions that define the ranges to find permissible values within the system to be created. In power systems, constraints can include power flow and transformer limits, the maximum power output of a unit, or ensuring that generation and demand are equal.

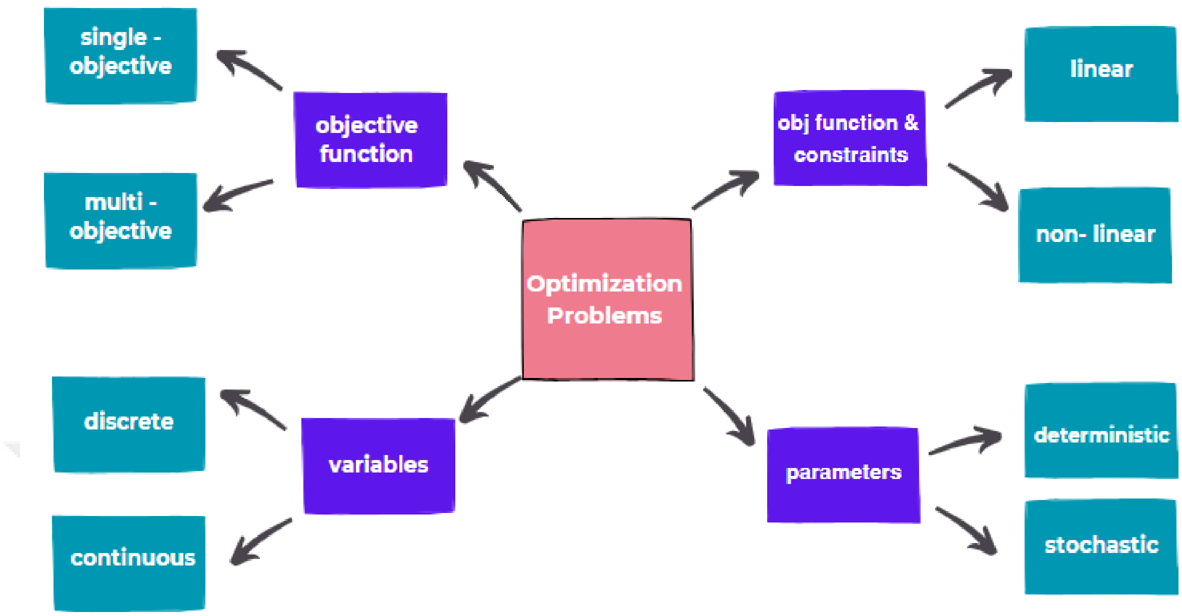

Figure 21: Overview of optimization problems.

Optimization problems can be grouped based on various criteria and attributes, as shown in Figure 21. The primary way to classify them is through the mathematical nature of their objective functions and constraints. Optimization problems can generally be divided into the following types:

- Linear vs. Non-Linear Optimization: When the objective function and constraints are linear, the problem is a linear optimization problem. If either the objective function or any constraint is non-linear, the problem is considered non-linear optimization.

- Discrete vs. Continuous Optimization: This categorization depends on the values the variables can take. In discrete optimization, variables are limited to a finite or countable set of values, such as in integer programming. Continuous optimization allows variables to take any value within a specified range.

- Deterministic vs. Stochastic Optimization: Deterministic optimization problems have parameters that are known and fixed. Stochastic optimization involves parameters that are random variables with uncertain values.

- Single- vs. Multi-objective Optimization: Typically, optimization problems involve a single objective function that needs to be maximized or minimized. However, multi-objective optimization involves multiple objective functions that may conflict with one another, requiring a balanced approach to find an optimal solution. In the application part, multi-objective problems usually either create a weighted combination of different objectives or are reformulated as single-objective problems by replacing some objectives with specified constraints.

Understanding these different types of optimization problems enhances the ability to effectively apply optimization theory to solve a wide range of complex real-world challenges. Once the first step of optimization, which is modeling the problem, is completed and appropriate solution methods for the problem should be researched. Optimization techniques are shown in Figure 22 [47].

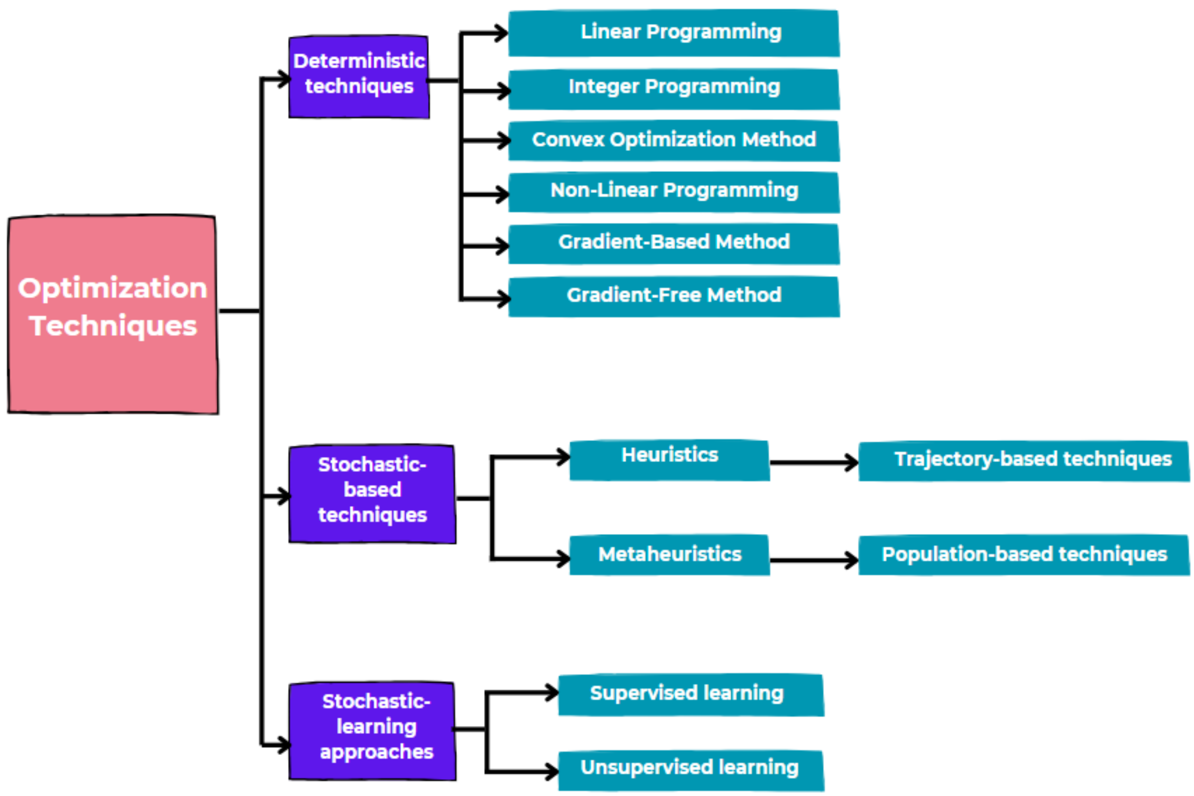

Figure 22: Classification of optimization techniques.

Deterministic techniques and stochastic techniques are two distinct approaches used to solve optimization problems, each with unique characteristics and applications. Deterministic techniques deal with problems where all parameters and variables are known with certainty and remain fixed, making the outcome predictable and reproducible. Common methods in deterministic optimization include LP and integer programming (IP), which are often applied in manufacturing processes and resource allocation. In contrast, stochastic techniques address problems involving uncertainty in parameters or the environment, typically modeled using probability distributions. This approach must adapt to randomness and variability. Stochastic techniques, including these learning-based methods, are well-suited for scenarios such as financial planning and supply chain management. The key differences lie in the nature of parameters and the resulting complexity and solution methods required to handle these variations.

One of the primary difficulties with Non-Linear Programming (NLP) is the presence of multiple local optima, which may not correspond to the global optimum. For instance, when attempting to locate the lowest point on a surface, one might end up in a shallow valley rather than the deepest one. This issue means that NLP may not ensure the quality or uniqueness of the solution, often necessitating several runs with different initial conditions. Additionally, NLP can be highly sensitive to the chosen method, parameters, or initial guess, which can impact the convergence rate, speed, and accuracy of the solution.

Methods for solving general NLP can be broadly categorized into analytic and numeric approaches [48]. Analytically, the Karush-Kuhn-Tucker (KKT) conditions provide necessary conditions for optimality under differentiability and constraint qualifications [49]. Numerically, solving KKT conditions is often impractical, for that reason iterative methods are used, starting from an initial point and updating using zero-order (objective and constraint values), first-order (gradients), or second-order (Hessians) information [50]. Third-order routines are generally avoided due to their computational complexity. Moreover, branch and bound techniques can be employed, subdividing the problem into smaller convex or linear approximations to find lower bounds on the overall cost [51].

Generally, optimization problems in power systems are non-linear, non-convex, and large-scale [52],[53],[54]. However, using non-linear terms typically increases the computational complexity and time required to solve the optimization model. Transformation approaches and linearization methods aim to reduce the computational complexity of the original non-linear models. Frank–Wolfe Algorithm [55], Piecewise linear approximation functions and Log-linearization via Taylor series approximation [56] can be listed as linearization methods of non-linear problems.

3.2 Linear Programming

LP is a technique that presumes the relationships between decision variables, constraints, and the objective function are linear. Typically, an LP problem involves minimizing a linear objective function composed of continuous real variables, subject to linear constraints. For clarity and simplicity in explanation and algorithm analysis, the problem is frequently presented in its standard form as follows:

$$
\begin{aligned}
&\text{minimize } c^T x \\
\text{subject to:}& \\
&Ax = b \\
&x \geq 0
\end{aligned}
\tag{3.2}
$$

Here, x represents the vector of unknown variables, c is the cost vector, and A is the constraint matrix. Generally, the matrix A is not square, meaning solving the LP isn't straightforward like inverting A. Typically, A has more columns than rows, indicating that A is under-determined, providing significant flexibility in choosing x to minimize within the feasible region.

The feasible region is a polyhedron defined by the set:

$$\{x \in \mathbb{R}^n \mid Ax = b, x \geq 0 \tag{3.3}$$

Any assignment of values to the decision variables constitutes a solution; a feasible solution should meet all constraints. An optimal solution is a feasible one that minimizes the objective function at most. An LP problem can have one, multiple, or no optimal solutions. There are no optimal solutions if there are no feasible solutions or if the constraints cause the objective function to be unbounded.

LP's strength lies in its versatility and the existence of general-purpose algorithms for finding optimal solutions. These methods are adept at handling any LP, regardless of its origin or specific structure. They offer both speed and reliability across a wide range of problem sizes and applications.

While converting all linear programs to a standard form is possible, it's often unnecessary to solve them. Most LP solvers can handle variations such as:

- General Bounds: $l \leq x \leq u$, These constraints allow for variables to have known lower l and upper u limits, represented as a vector.

- Two-Sided Constraints: $b_1 \leq Ax \leq b_2$, These constraints express a range within which a linear combination of variables Ax must fall, defined by two arbitrary values $b1$ and $b2$.

- Maximization Problems: Maximization problems can be converted to minimization problems by multiplying the objective function vector c by negative one -1.

Today, two primary techniques are widely used: the Simplex method [55] and the Barrier (or interior-point) method [57]. Both methods iteratively refine candidate solutions until the optimal one is identified. The Simplex method, introduced by George Dantzig in the 1940s [57], works by finding feasible solutions that adhere to all constraints. This is achieved by setting enough variables to their boundary values and transforming the constraint system into a square system of equations. Each feasible solution represents a vertex at the boundary of the feasible region defined by the constraints.

The last point for this section is to mention the solution of linear problems. Every linear program has a corresponding dual linear program closely tied to it. Both the primal and dual programs are based on the same cost and constraint coefficients but structured such that if one is a minimization problem, the other becomes a maximization problem [58]. The optimal values of their objective functions, when finite, are equal. The dual problem's variables can be seen as prices related to the primal problem's constraints, providing an economic interpretation of the dual whenever the primal has one. These prices can also be called as *'shadow prices'*, for a specific constraint represents the variation in the optimal value of the objective function for each unit increase in the constraint's right-hand side value, assuming all other problem data remain constant [55].

The asymmetric form of the primal-duality relation is given in the Eq (3.4) [59].

$$\begin{aligned} \text{Primal} \quad & \quad \text{Dual} \\ \text{minimize } c^T x \quad & \quad \text{maximize } y^T b \\ \text{subject to:} \quad & \quad \text{subject to:} \\ Ax = b, \quad x \geq 0 \quad & \quad y^T A \leq c^T \end{aligned} \tag{3.4}$$

It is important to note that shadow prices are linked to the constraints of the problem, not the variables [55]. Essentially, they reflect the marginal value of adding one more unit to a particular right-hand side value. Analyzing a problem from both the primal and dual perspectives often yields computational benefits and economic insights.

3.3 Programming in Power System

The optimization in power systems has progressed significantly alongside advances in computing and optimization theory. During the first half of the 20th century, the OPF problem was addressed by skilled engineers and operators relying on their expertise and practical rules. Over time, computational tools began to supplement the operators' intuition. The OPF problem was formally defined in the 1960s by Carpentier (1962), yet it remains a challenging problem to solve. While linear solvers are readily available for linearized versions of the OPF problem, nonlinear solvers fall short in providing global optimum solutions, lack robustness, and are too slow for practical use [60]. In electricity control rooms, the OPF problem or its approximations must be resolved multiple times a day, often as frequently as every 5 minutes.

The subsequent sections will discuss three common problems in power systems: ED, power flow (load flow), and OPF.

3.3.1 Economic Dispatch

The goal of ED is to determine the optimal output levels for all generation units in a power system to minimize fuel costs while adhering to system constraints [61]. It involves allocating generation among committed units to meet energy requirements while satisfying imposed constraints. In an interconnected power system, economic power dispatch involves scheduling the total real and reactive power output of each power plant to minimize operating costs. This entails adjusting the generator's real and reactive power within specific limits to meet demand at the lowest fuel cost.

ED can be divided into two stages: Unit Commitment(UC) and Unit Dispatch (UD). UC occurs before real-time operation, determining which generating units will be available. UD happens in real-time, specifying the amount of generation required from each available unit [61].

The objective of ED is to determine the total power generation output that minimizes operating costs. In addition to this main objective, several other objectives include such as reducing emissions, maximizing profit, or maintaining system stability [61].

$$\min \sum_i c_i P_{Gi} \tag{3.5}$$

subject to:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max}, \quad \forall i \tag{3.6}$$

$$\sum_i P_{Gi} = P_D \tag{3.7}$$

Considering the constraints of the ED model, it is seen that demand must be equal to generation by complying with the maximum and minimum capacities of power generation resources. This means that ED does not consider any network flows. The assumption is a copperplate network, i.e. a lossless and unrestricted flow of electricity from A to B [62]. Such a simple model can be solved even on paper, without the need for a solver, by sorting the resources available in the system according to their service capacity and matching them with the electricity demand. It should also be noted that as the generator sources in the system differ, factors such as the ramp-up/down capability of generators, minimum/maximum time of generators, or the uncertainty of RESs make this problem difficult, but a simple solution to the ED problem with 'Merit Order' is given in Figure 23.

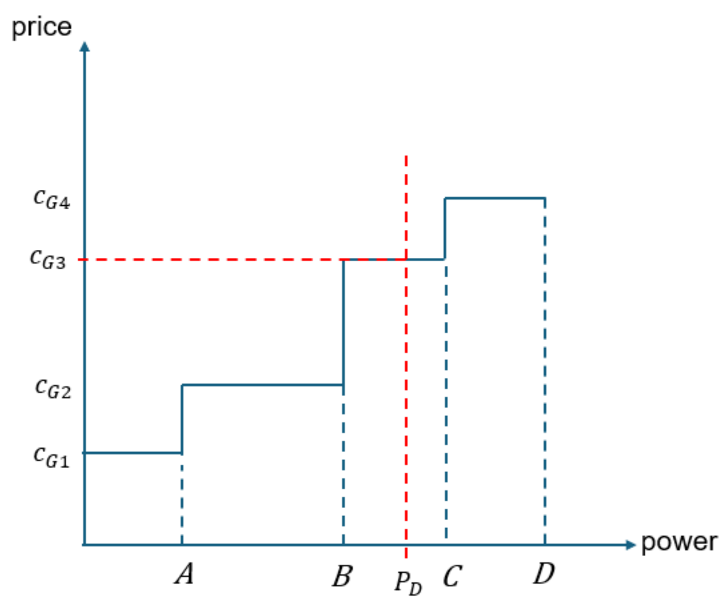

Figure 23: Typical Merit-Order Curve.

The idea behind the 'Merit Order' is to order generators according to the price of their UC capacity and find the 'marginal price' when the existing demand matches the generator capacity. In Figure 24, c_{G3} is the marginal price and G_3 is the marginal generator, G_1 and G_2 are the generators that will be fully dispatched while G_4 will not be dispatched.

ED involves planning conducted in energy markets before real-time operations take place [63]. However, in real-time operations, it is unlikely for the cheapest generator to meet the entire demand on its own, even if it does not exceed its own upper limit. This is because transmission lines, which transport the generated power in power grids, have physical carrying limits. Since the power flowing through these transmission lines must stay within certain limits, the ED problem needs to be updated according to these line flow constraints.

3.3.2 Optimal Power Flow

The set of optimization problems in electric power systems engineering known as OPF is one of the most significant and extensively studied areas within constrained nonlinear optimization. Carpentier (1962) introduced OPF as an extension of the ED problem in electric power systems. Carpentier's major contribution was incorporating the electric power flow equations into the ED formulation [63]. Today, the defining characteristic of OPF remains the inclusion of power flow equations within the set of equality constraints. OPF encompasses any optimization problem that aims to optimize the operation of an electric power system while adhering to the physical constraints dictated by electrical laws and engineering limits.

Power grids are made up of two primary elements: buses, which correspond to crucial points in the grid (such as generation points, load points, and substations), and transmission (or distribution) lines that link these buses (seen in Figure 24.) [64].Each branch in the network symbolizes a physical conductor connecting two buses (nodes). The resistance and reactance of these conductors result in differences between the sending and receiving ends of the branch. Additionally, there is a maximum amount of power that a conductor can transfer. Typically, the thermal limit pertains to the apparent power flow, which is calculated from both real and reactive (imaginary) power flows. Given the bidirectional nature of power flow in systems, this constraint must be modeled for both directions: from Bus i to Bus j and from Bus j to Bus i [65]. Before moving on to the equations, it is important to note that power transmission is more efficient at high voltages. Higher voltage (or correspondingly lower current) minimizes power loss through distributing along transmission lines. Additionally, power grids typically employ AC because its voltage can be easily adjusted (from high to low) using transformers.

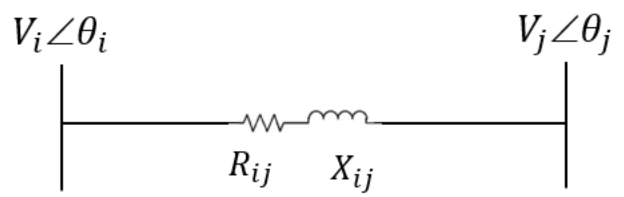

Figure 24: Simplified model of the line representation.

Power systems are generally controlled by setting four individual quantities for each bus to satisfy both Kirchhoff's laws and the system's operational limits. These quantities are real power generation, reactive power generation, voltage magnitude, and voltage angle [65]. Any values of these quantities that meet the energy balance equation and their physical limits constitute a feasible, stable, and reliable operational state of the power system. However, modern power systems incorporate multiple generators that produce energy. The resulting mathematical problem, known as AC OPF, can be formulated as a NLP. AC OPF problem is presented in (3.8)-(3.14) without considering time intervals; however, the model must satisfy all constraints are met at each time interval [65].

Model 1: AC OPF

$$\text{minimize} \quad \sum_g f_g(P_g) \tag{3.8}$$

subject to:

$$P_{gi} - P_{di} = \sum_j |V_i||V_j|(G_{ij}\cos(\theta_i - \theta_j) + B_{ij}\sin(\theta_i - \theta_j)) \quad \forall i \tag{3.9}$$

$$Q_{gi} - Q_{di} = \sum_j |V_i||V_j|(G_{ij}\sin(\theta_i - \theta_j) - B_{ij}\cos(\theta_i - \theta_j)) \quad \forall i \tag{3.10}$$

$$|V_i|^{\min} \leq |V_i| \leq |V_i|^{\max} \quad \forall i \tag{3.11}$$

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max} \quad \forall i \tag{3.12}$$

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max} \quad \forall i \tag{3.13}$$

$$|S_{ij}| \leq S_{ij}^{\max} \quad \forall (i, j) \text{ and } (j, i) \tag{3.14}$$

The objective function is the same as that of ED, which is to minimize the generation cost. (3.9) is the nodal power balance for each node for real power and (3.10) for reactive power. In other words, production minus demand is the constraint that makes it equal to the power flowing from that bus to the other buses to which that bus is connected. The constraints between (3.11) - (3.14) are the minimum and maximum limits for voltage magnitude, real, reactive and apparent power, respectively.

OPF is characterized as a non-linear and non-convex optimization challenge. The interior-point method is among the most effective techniques for tackling large-scale optimization issues of this nature [66]. Despite its effectiveness, the interior-point method is computationally expensive, with the required time scaling super linearly with the size of the system. To mitigate this issue, several strategies have been developed. These include simplifying the original OPF problem through techniques like convex relaxation [67] or finding approximate solutions using methods such as DC approximation [68], which will be discussed in the following section.

3.3.3 DC Optimal Power Flow

The comprehensive mathematical model, as outlined in Model 1, is too complex for practical use in real power system operations such as solving OPF for large-scale transmission networks. The constraints in the DC Optimal Power Flow (DC OPF) problem are linear approximations of the actual nonlinear AC power flows. These DC approximations stem from various physical assumptions and observations.

1. In transmission networks, the line resistance R_{ij} is generally much lower than the line reactance X_{ij}, leading to an approximation of B_{ij} as -1/ X$_{ij}$. This aligns with the assumption that $G_{ij} = 0$ for the transmission system.

2. The voltage phase angle difference between any two buses is usually small, typically not exceeding 30 degrees. Hence, the small angle approximation can be applied, where $sin(\theta_i - \theta_j) \approx \theta_i - \theta_j$ and $cos(\theta_i - \theta_j) \approx 1$

3. At the transmission level, voltage magnitudes $|V_i|$ and $|V_j|$ are generally very close to 1.0 per unit during normal operation.

Finally, based on these initial assumptions and considering that reactive power is a localized phenomenon unable to travel long distances, it can be observed that the magnitude of reactive power flow on the lines Q_{ij} for line ij) is significantly less than that of active power flow P_{ij} for line ij). Using these assumptions, the DC OPF problem can be written as follows:

Model 2: DC OPF

$$\text{minimize} \quad \sum_g f_g(P_g) \tag{3.15}$$

subject to:

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max} \quad \forall i \tag{3.16}$$

$$f_k = B_{fk} \cdot (\theta_i - \theta_j) \quad \forall k \tag{3.17}$$

$$P_{gi} - P_{di} = \sum_{k \in i,*} f_{k,t} - \sum_{k \in *,i} f_{k,t} \quad \forall i \tag{3.18}$$

$$-f_k^{\max} \leq f_k \leq f_k^{\max} \quad \forall k \tag{3.19}$$

where f_k denotes the maximum allowable line flow for line k that connects bus i to bus j. It is important to note that the maximum current determines the physical limitation on transmission line flows the line can safely carry [69].

3.3.4 Locational Marginal Pricing

The decision-making process in the OPF problem, which determines the optimal dispatch of generation resources, traditionally aligns with centralized operations and vertically integrated (monopoly) electric utilities. With the deregulation of the electric utility sector, this centralized decision-making has transitioned to liberalized electricity markets [70]. In these markets, nodal pricing is used to account for system constraints and losses. Power flow limitations in a congested grid restrict trades, and electrical losses affect the balance of supply and demand, leading to locational (nodal) prices for electric power. In a market with perfect competition, where all participants are price takers without market power, the optimal nodal prices equal the LMPs. The marginal price of active power at a bus represents the cost of serving an increment of load by the least expensive generation means, reflecting the sensitivity of the minimum total generation cost to load variations. Thus, LMPs are closely related to cost-minimizing OPF problems and quantify the sensitivity of the optimal objective value of the OPF problem to the nodal power balance constraints.

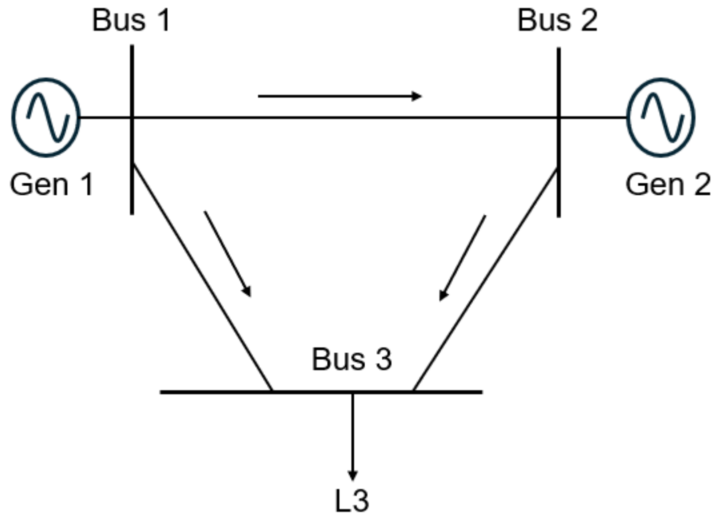

Figure 25: 3-bus system representation.

LMP refers to the incremental cost of purchasing electricity when a 1 MW load is added to a node, with the system meeting the demand in the most economical way. In the 3-node system depicted in Figure 25, the system load is fixed, and the market is cleared with the objective of minimizing electricity purchase costs. As shown in Figure 25, when the load L3 increases by 1 MW, the marginal cost must be calculated. The constraints of the 3-node system include Kirchhoff's laws of voltage and current, the capacities and unit generation costs of generators Gen 1 and Gen 2, and the maximum power flow capacities on branches 1-2, 1-3, and 2-3. Based on these constraints, the most economical incremental output allocation for Gen 1 and Gen 2 is determined when the load L3 increases by 1 MW, thereby obtaining the LMP for the load L3 node.

Accurate LMPs are generally difficult to obtain due to the non-convex nature of the OPF problem. As a result, LMPs are often determined using a simplified and linearized system model for AC grids known as the "DC power flow," as discussed previously. The OPF formulation based on the "DC power flow" is referred to as "DC OPF" and is a linear program. Due to the strong duality in linear programs, the approximation of LMPs is derived from the Lagrangian dual variables of the power balance constraints, which can be efficiently computed using methods like the interior-point method. In the previous subsection, DC OPF Model is given as a lossless form, however, 'losses' can be added to the system with 'Loss Factor' and 'Delivery Factor' [71]. Additionally, 'iterative DC OPF' models are available in the literature as well [72].

When the duals of equations (3.9) and (3.18) in the OPF equations given in Model 1 and Model 2 are found, the LMP at each node is obtained. Since these power balance equations are provided separately for each node, the shadow prices obtained are locational. Reactive LMPs are not that popular in the electricity markets, for this reason, (3.10) and (3.19) are not in the scope of Lagrangian calculations. Addition to Model 1 and Model 2, LMPs can also be achieved by solving the Security Constrained which is formulated based on the DC OPF model without considering network losses:

Model 3: Security Constrained Economic Dispatch

$$\text{minimize} \quad \sum_i C_i(P_{gi}) \tag{3.20}$$

subject to:

$$\sum_i P_{gi} = \sum_i P_{di} \quad : \lambda \tag{3.21}$$

$$\sum_i T_{l,i} P_{gi} - \sum_i T_{l,i} P_{di} \leq F_l^{\max} \quad : \mu_l^+ \tag{3.22}$$

$$-\sum_i T_{l,i} P_{gi} + \sum_i T_{l,i} P_{di} \leq -F_l^{\max} \quad : \mu_l^- \tag{3.23}$$

$$P_{gi} \leq P_i^{\max} \quad : \nu_i^+ \tag{3.24}$$

$$-P_{gi} \leq -P_i^{\max} \quad : \nu_i^- \tag{3.25}$$

LMP is defined as the incremental cost to serve an additional megawatt at each node while adhering to all security constraints. Mathematically, the LMP is derived from the partial derivative of the optimal value function of the ED model with the nodal load as the parametric variable. Let $C^*(P_d)$ represent the minimum operating cost function with respect to the nodal load P_d; then the LMP at node i is given by [73]:

$$
\begin{aligned}
\mathrm{LMP}_i = \frac{\partial C^*(P^d)}{\partial P_i^d} &= \frac{\partial C^*(P^d)}{\partial \sum P_i^d}\frac{\partial \sum P_i^d}{\partial P_i^d} \\
&+ \frac{\partial C^*(P^d)}{\partial \left(\sum T_{l,i}P_i^d + F_l^{\max}\right)}\frac{\partial \left(\sum T_{l,i}P_i^d + F_l^{\max}\right)}{\partial (P_i^d)} \\
&+ \frac{\partial C^*(P^d)}{\partial \left(-\sum T_{l,i}P_i^d + F_l^{\max}\right)}\frac{\partial \left(-\sum T_{l,i}P_i^d + (-F_l^{\max})\right)}{\partial (P_i^d)} \\
&= \lambda + \sum_l (-\mu_l^+) T_{l,i} + \sum_l \mu_l^- T_{l,i} \\
&= \underbrace{\lambda}_{\textbf{(energy price)}} + \underbrace{\sum_l T_{l,i}(-\mu_l^+ + \mu_l^-)}_{\textbf{(congestion price)}}
\end{aligned}
\tag{3.26}
$$

As shown in Equation (3.26), the LMP is ultimately represented by the optimal dual variables of constraints (3.21)-(3.23), reflecting the sensitivity of the optimal objective function to the right-hand terms of these constraints [73]. The optimal dual variable of the power balance Equation (3.21) is the energy component of the LMP, indicating the marginal cost of producing electricity without any constraints and is the same across all nodes. The second term in the final LMP representation is the congestion component, which indicates the marginal cost to maintain transmission capacity constraints. If network losses are considered, another component corresponding to power losses is included in the LMP formulation. Modeling this power loss component is complex yet crucial and has been extensively studied in the literature using various methods, such as sensitivity-based methods [74], piecewise linear modeling [75], and linear equation-based methods [76].

3.4 Distribution Locational Marginal Pricing

Associated with the emerging research on distribution-level markets is the imperative to enhance the pricing mechanism for distribution market operations. This mechanism should possess the following characteristics: 1) alignment with the existing wholesale market; 2) incentives for the proper operation and development of Distributed Energy Resources (DER); 3) reflection of the cost and physical operating conditions of the distribution system; and 4) rewards for DERs providing flexibility and grid services. These features will promote the smooth integration of DERs into distribution networks [77].

At the transmission level, the predominant pricing method is LMP, which is widely implemented across the United States. The LMP fundamentally represents the marginal cost of energy supply, active transmission security constraints, and transmission losses at each system bus. This provides a useful reference for distribution networks as well. Numerous studies have aimed to extend LMP to DLMP to capture the temporal and spatial values of electricity [77]. The concept of DLMP, or distribution-level nodal pricing, was first proposed to distinguish it from the DC OPF-based pricing by accounting for network losses [78]. The value of the distributed generator (DG) was quantified through the reduction of line losses and loading. Subsequent DLMP developments included energy, congestion, and power loss components to drive controls in a distribution system utilizing electronic devices [79]. Additionally, DLMP was extended to include voltage components by considering voltage constraints, rewarding DERs for contributions to voltage support and loss reduction [80]

The success of distribution markets depends on the interplay between various participants. Their bidding and offering strategies, combined with the physical constraints of the distribution network (such as capacity limitations and voltage regulation), determine the overall market efficiency and security. The typical market-clearing model is given in Model 4:

Model 4: Typical Market Clearing Model

$$\text{minimize} \quad \sum_{i \in \Omega_G} f(P_i^G, \hat{Q}_i^G) \tag{3.27}$$

subject to:

$$\sum_{i \in \Omega_G} P_i^G - \sum_{i \in \Omega_N} P_i^D - P^{\text{loss}} = 0 \quad : \lambda^p \tag{3.28}$$

$$\sum_{i \in \Omega_G} Q_i^G - \sum_{i \in \Omega_N} Q_i^D - Q^{\text{loss}} = 0 \quad : \lambda^q \tag{3.28}$$

$$S_l^{\min} \leq S_l \leq S_l^{\max} \quad : \omega_{s,l}^{\min},\ \omega_{s,l}^{\max} \quad \forall l \in \Omega_L \tag{3.30}$$

$$V^{\min} \leq V_j \leq V^{\max} \quad : \omega_{v,j}^{\min},\ \omega_{v,j}^{\max} \quad \forall j \in \Omega_N \tag{3.31}$$

$$P_i^{\text{G,min}} \leq P_i^G \leq P_i^{\text{G, max}} \quad : \omega_{p,i}^{\min},\ \omega_{p,i}^{\max} \quad \forall i \in \Omega_G \tag{3.32}$$

$$Q_i^{\text{G,min}} \leq Q_i^G \leq Q_i^{\text{G, max}} \quad : \omega_{p,i}^{\min},\ \omega_{p,i}^{\max} \quad \forall i \in \Omega_G \tag{3.33}$$

$$-Q_{G_i} \leq \hat{Q}_{G_i},\ Q_{G_i} \leq \hat{Q}_{G_i} \quad : \kappa_i^-,\ \kappa_i^+ \quad \forall i \in \Omega \tag{3.34}$$

The objective of equation (3.27) is to minimize the overall cost of electricity generation, including expenses from purchasing electricity on the wholesale market and costs associated with DG. Equations (3.28) and (3.29) ensure the balance of active and reactive power, respectively. Equation (3.30) addresses network congestion constraints, while equation (3.31) ensures voltage levels stay within the required limits.

Equations (3.32) and (3.33) define the permissible ranges for the active and reactive power outputs of generators. In equation (3.34), $\hat{Q}_{G_i} = |G^g_{i,t}|$ is utilized to account for the costs involved in both the absorption and generation of reactive power. The set of equations from (3.27) to (3.34) outlines a fundamental market-clearing model. This model can be expanded to cover multiple time periods by adding constraints that link different time slots and can be adapted to include additional constraints and specific operating conditions for more complex scenarios [77].

For linearization, the non-linear AC OPF model is transformed into a linear model through specific assumptions. A commonly employed approach is the linearized DistFlow model [81], which ignores power loss and voltage angle. [82] proposed a modified DistFlow model that uses the ratios of active and reactive power to voltage magnitude as state variables, allowing power flows and voltage magnitudes to be expressed in matrix form by incorporating the path-branch incidence matrix.

Based on equations (3.27) to (3.34), the Lagrangian function of Model 4 can be expressed as follows:

$$\begin{aligned}
L = &\sum_{i\in\Omega_G} f(P^G i, \hat{Q}^G_i) \\
&- \lambda^p \left(\sum_{i\in\Omega_G} P^G_i - \sum_{i\in\Omega_N} P^D_i - P^{\text{loss}} \right) \\
&- \lambda^q \left(\sum_{i\in\Omega_G} Q^G_i - \sum_{i\in\Omega_N} Q^D_i - Q^{\text{loss}} \right) \\
&- \sum_{l\in\Omega_L} \omega^{\text{s,min}}_l (S_l - S^{\text{min}}_l) \quad - \sum_{l\in\Omega_L} \omega^{\text{s,max}}_l (S^{\text{max}}_l - S_l) \\
&- \sum_{j\in\Omega_N} \omega^{\text{v,min}}_j (V_j - V^{\text{min}}) \quad - \sum_{j\in\Omega_N} \omega^{\text{v,max}}_j (V^{\text{max}} - V_j) \\
&- \sum_{i\in\Omega_G} w_i \cdot g_i(x)
\end{aligned} \tag{3.35}$$

where $g_i(x)$ denotes the power output constraints in equations (3.32)–(3.34). The active power DLMP and reactive power DLMP are obtained by taking the first-order partial derivatives of the Lagrangian function with respect to the active and reactive load demands, respectively.

$$
\begin{aligned}
\pi_i^p = \frac{\partial L}{\partial P_i^D} &= \lambda^p + \lambda^p \cdot \frac{\partial P^{loss}}{\partial P_i^D} + \lambda^q \cdot \frac{\partial Q^{loss}}{\partial P_i^D} \\
&+ \sum_{l \in \Omega_L} (\omega_l^{s,\max} - \omega_l^{s,\min}) \cdot \frac{\partial S_l}{\partial P_i^D} \\
&+ \sum_{j \in \Omega_N} (\omega_j^{v,\max} - \omega_j^{v,\min}) \cdot \frac{\partial V_j}{\partial P_i^D} \qquad (3.36) \\
\pi_i^q = \frac{\partial L}{\partial Q_i^D} &= \lambda^q + \lambda^q \cdot \frac{\partial Q^{loss}}{\partial Q_i^D} + \lambda^p \cdot \frac{\partial P^{loss}}{\partial Q_i^D} \\
&+ \sum_{l \in \Omega_L} (\omega_l^{s,\max} - \omega_l^{s,\min}) \cdot \frac{\partial S_l}{\partial Q_i^D} \\
&+ \sum_{j \in \Omega_N} (\omega_j^{v,\max} - \omega_j^{v,\min}) \cdot \frac{\partial V_j}{\partial Q_i^D} \qquad (3.37)
\end{aligned}
$$

where π_i^p and π_i^q refer to the active DLMP and reactive DLMP at node i, respectively.

The active DLMP consists of four components:

$$
\text{DLMP}_i = \lambda_e + \lambda_{C,i} + \lambda_{L,i} + \lambda_{V,i} \qquad (3.38)
$$

- Energy term (λ_e), indicating the marginal cost of producing an extra MWh, representing the marginal energy cost at the reference bus. This additional cost can be decomposed into a subset of shadow costs linked with the binding constraints for that node.

- Congestion term (λ_C), signifying the marginal cost incurred due to congestion within distribution networks.

- Loss term (λ_L), representing the marginal cost attributed to active power loss within distribution systems

- Voltage support term (λ_V) is related to cost that maintains the voltage within the acceptable level. If the voltage constraints at a node are not binding, it will be zero.

The marginal price signifies the incremental cost of delivering the next MWh of electricity. This cost can be broken down into the shadow costs associated with the binding constraints at that node. The marginal energy price is determined by the marginal unit in the distribution system. The marginal congestion price indicates the marginal cost of congestion at a given node. However, congestion rarely occurs in traditional radial distribution networks, which feed from one point. Opposed to transmission systems in which loss is insignificant in comparison to other components of LMPs, such as the cost of providing energy and cost of congestion, losses cannot be negligible in the calculation of LMP in distribution networks due to their high resistance to inductance ratio and low voltages [83]. The voltage support price covers the cost of keeping voltage within acceptable limits, and it will be zero if the voltage constraints at a node are not binding. The pricing of reactive power has been debated. In [80], the concept of reactive DLMP, a potential method for pricing reactive power, was introduced. If reactive LMP is not considered in the transmission network, it is set to zero at the power supply point; if it is considered, as with the Q-LMP, equation (3.37) can be used to calculate the reactive DLMP. It's important to note that the formulation in equations (3.36) and (3.37) is based on the standard market model (3.27) - (3.34). Additional price components, like the marginal imbalance price, can be included when other constraints are factored in. By all DLMP parameters, loss is a key variable that requires attention to be allocated fairly among the market participants. Numerous studies have been conducted for loss allocation both in transmission and distribution networks [84].

LMP and DLMP share many similarities in both their derivation and physical meaning. Both involve the combination of shadow prices of binding constraints and reflect the marginal cost at a node. However, key differences arise due to the physical distinctions between transmission and distribution networks, which can be outlined in the following four titles [77]:

1. Congestion: Line congestions are more common in transmission networks because of their meshed structure and the large-scale electricity transactions they handle. In contrast, feeders in radial distribution networks are typically designed to handle peak power flow, making congestion rare. However, with the increasing integration of DERs and potential network reconfigurations, power flow patterns in distribution networks might change, leading to congestion issues similar to those in transmission systems.

2. Power Losses: Distribution lines usually have a higher R/X ratio, resulting in a greater power loss factor compared to transmission lines. Therefore, power losses are significant at the distribution level, while they are often negligible in transmission networks where DC OPF is used.

3. Voltage: Voltage drops are more problematic in distribution systems due to their radial topology and long feeders. Additional measures are required to keep the system voltage within acceptable limits, and these costs should be reflected in DLMP. On the other hand, the wholesale LMP model typically assumes a flat voltage magnitude in the DC OPF model.

4. Imbalance: Imbalance is a characteristic of distribution systems, which often require models that can handle multiple phases and include the costs of strategies to mitigate imbalance. Transmission systems, in contrast, are generally balanced.

An accurate DLMP model should be adaptable to incorporate multiple phases and account for the costs of specific strategies aimed at mitigating imbalances. Besides the marginal energy price, the previous discussion highlights the differences and potential price components in LMP and DLMP. The number of price components in LMP or DLMP, however, is not constant. Depending on the application and the distribution network under consideration, certain pricing components may be excluded.

In [85] conducted an in-depth examination of three different methods for understanding DLMP, emphasizing its importance for policymaking in the development of future distribution markets. This and previous studies indicate that DLMP has attracted significant attention and that it effectively retains price characteristics and reflects both operational conditions and the value of DERs in a distribution system.

CHAPTER IV

IMPLICATIONS OF EVC-LOADS ON LMPS & DLMPS

Within the scope of the thesis, the spatial and temporal effects of charging electric vehicle loads on electricity prices at both the transmission level and the distribution level are examined. First, after using the 39-node transmission system and solving the DC OPF model, the effects of EV charging load on locational marginal prices are analyzed through 4 scenarios. Moreover, AC OPF is solved in a 34-bus distribution system, and the effects of EV charging load on distribution locational marginal prices are analyzed through 4 scenarios.

4.1 Implications of EV Charging Loads on LMPs

In this section, scenarios in Figure 26 have been created in which EVs are added to 3 different buses. The results are analyzed for each scenario by increasing the percentages of EVs in total demand. The results of all 4 scenarios are given together in Figure 26 for comparative discussion. Before examining the scenarios, the EV charging methodology used in the analysis is introduced.

The charging scheme aims to assess the effects of random charge of the EVs in the transmission system on LMPs. LMP is used to monitor congestion that the unpredictable behavior of EV owners may cause. In addition to this unexpected behavior of EV owners being an intertemporal problem, considering the flexibility of the drivers, the charging period of EVs should have a multiperiod framework. The methodology steps in Figure 27 are listed below to examine the LMP differences that may occur when EVs are charged at any time and the LMP changes at that time.

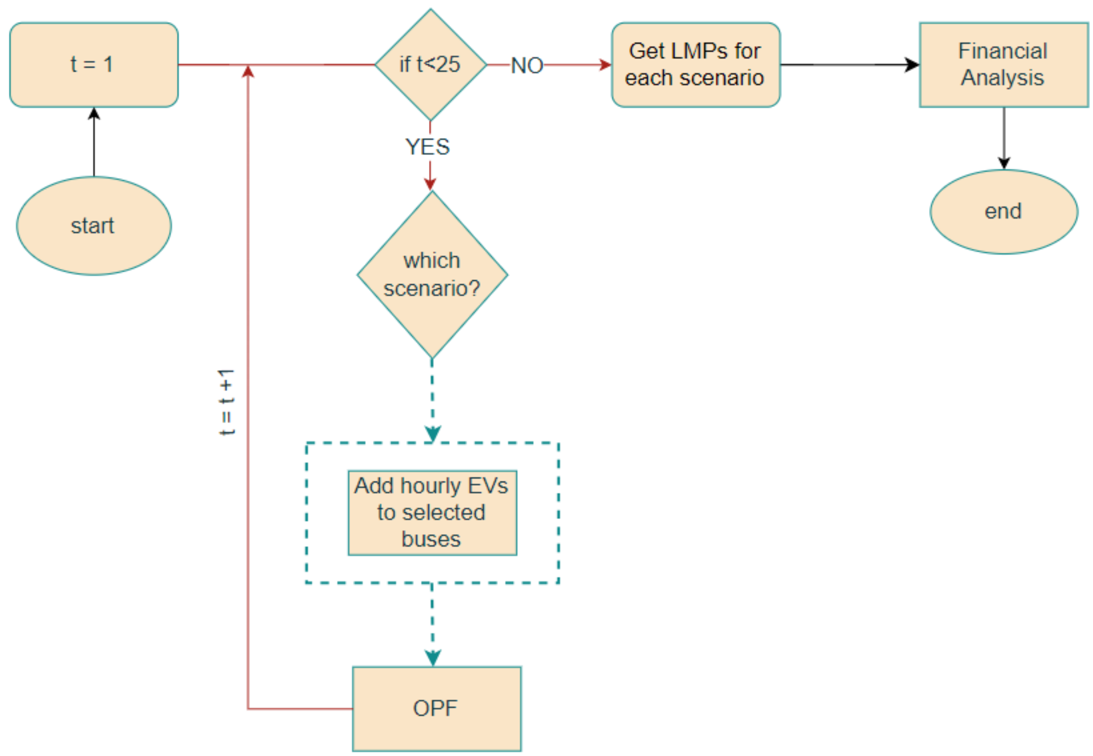

Figure 26: Illustration of the Methodology I.

First, OPF is run for a multiperiod (24 hours) in the base scenario. Each node has a LMP for every hour, and these prices are used for financial analysis. Then, for the scenarios, three EVs are added to buses, which are already selected for each scenario in the first place. The multiperiod-OPF is performed after these additional loads.

After getting LMPs for all scenarios, the financial analysis is performed based on the cost-to-load term. Since cost-to-load is calculated by multiplying the LMP of each bus with its demand, it can be called the cost of demand to an end user. Minimizing the cost-to-load by charging the EVs, that is, maximizing social welfare, will be discussed in the following sections.

4.1.1 Test Case 1: IEEE 39-Bus System

The IEEE 39-bus system, depicted in Figure 27, has been utilized as a case study, with technical details sourced from [86]. This loop transmission system comprises 29 demand nodes, with active demand present at 21 nodes. Demand values have been updated with the values with [87].

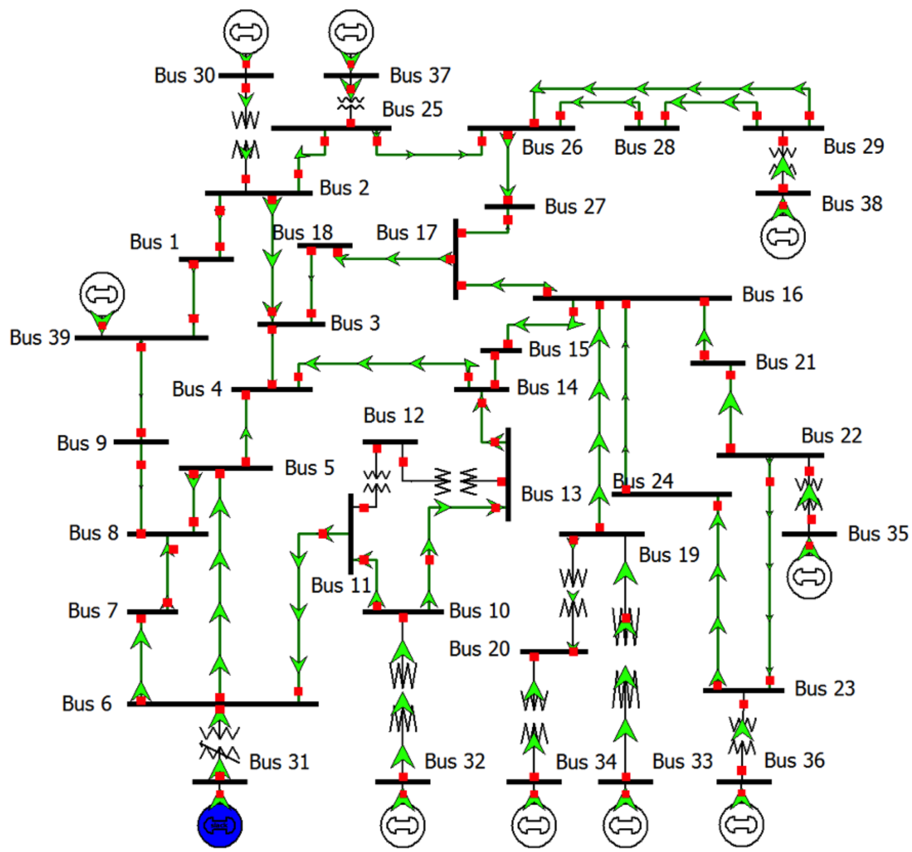

Figure 27: IEEE 39-bus system [86].

Technical parameters such as line flow limits, generator capacities, values of resistance and reactance have remained unchanged. The only changes made, in addition to updating the demands, are limited to adjusting the generator costs 'a' parameter, which was originally fixed in the reference tables, to reflect possible electricity market prices, while the 'b' parameter remained constant. Details regarding the generators are provided in Table 7.

Table 6: Generator specifications in the network.

Bus Number	Generator Type	Max Capacity	Generation Cost a	Generation Cost b
30	Hydro	1040	0.02	0.01
31	Nuclear 1	646	0.03	0.01
32	Nuclear 2	725	0.025	0.01
33	Fossil 2	652	0.01	0.01
34	Fossil 1	508	0.015	0.01
35	Nuclear 3	687	0.035	0.01
36	Fossil 3	580	0.01	0.01
37	Nuclear 4	564	0.022	0.01
38	Nuclear 5	865	0.028	0.01
39	External Grid	1100	0.005	0.01

4.1.2 Case Studies and Results

Scenarios created for the addition of a 40 kW EV charging load can be listed as follows:

1. Three buses with generators with the lower generation cost (brown circles in Figure 28.)
2. Three buses with the higher demand (blue circles in Figure 28.)
3. Three buses with lower positive demand (green circles in Figure 28.)
4. Three buses with the most connections (red circles in Figure 28.)

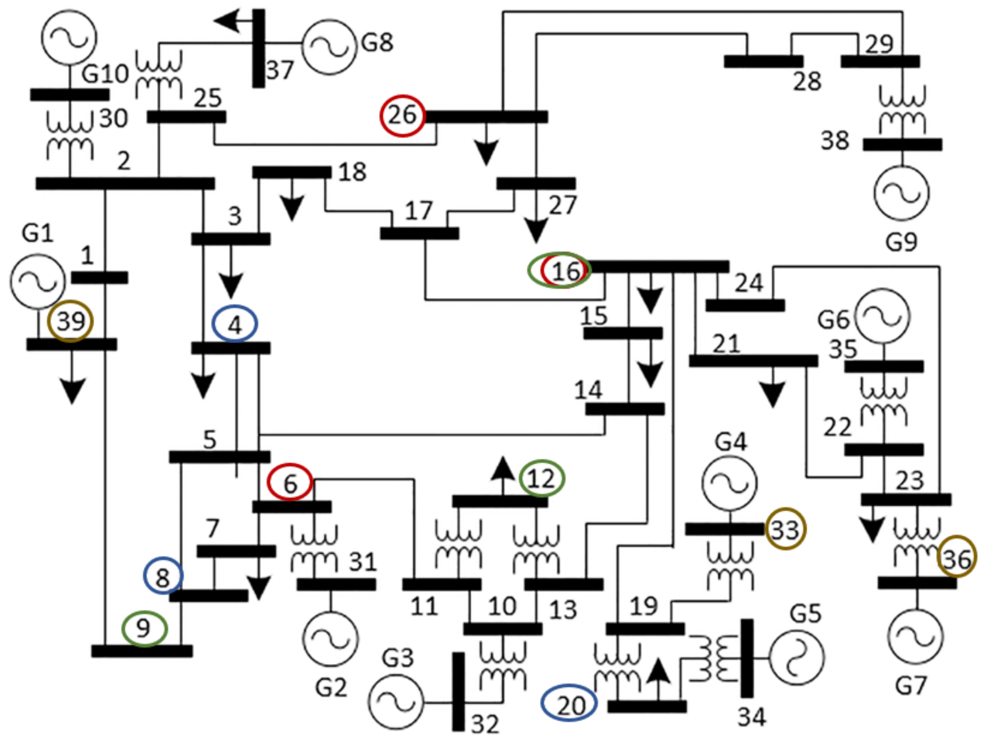

Figure 28: IEEE 39-bus system with selected buses for each scenario.

For all scenarios, while increasing the % of EV in total demand, LMP is also getting higher. LMPs before the addition of EVs are called base scenarios. In addition, the effect of charging EVs is most effective during peak times for all scenarios. Minimum LMPs are observed between 02:00 and 07:00, and maximum LMPs are observed between 10:00 and 14:00. The low-cost-gen scenario result is given in Figure 29 to demonstrate the general hourly LMP pattern for the overall system.

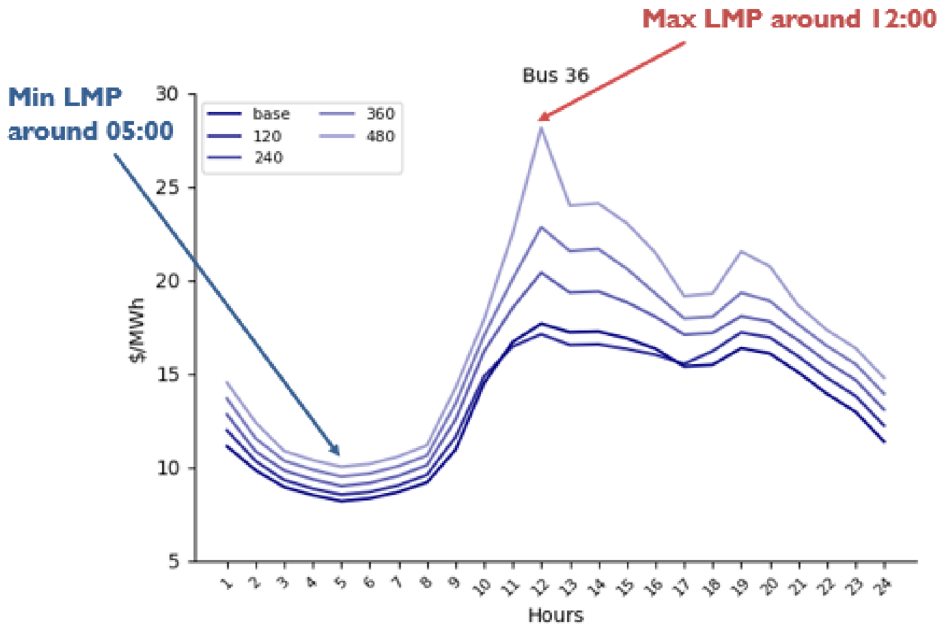

Figure 29: The general hourly LMP pattern for the overall system.

Moreover, the graphs from Figure 30 to Figure 33 include 24-hour cost-to-load graphs. Cost-to-load as formulated in (4.1) is the multiplication of the demand on a bus $d_{i,t}$ with the LMP $\lambda_{i,t}$ on that bus. It can simply be thought of as the value of that demand to the end-user.

$$\mathrm{CRL}_t = \sum_{i=1}^{N} \lambda_{i,t} \cdot d_{i,t}, \quad \forall t \tag{4.1}$$

The idea of distributing EVs to the buses where the cheapest generations are made is created to examine the change in price if EVs are charged in areas close to low-cost generations.

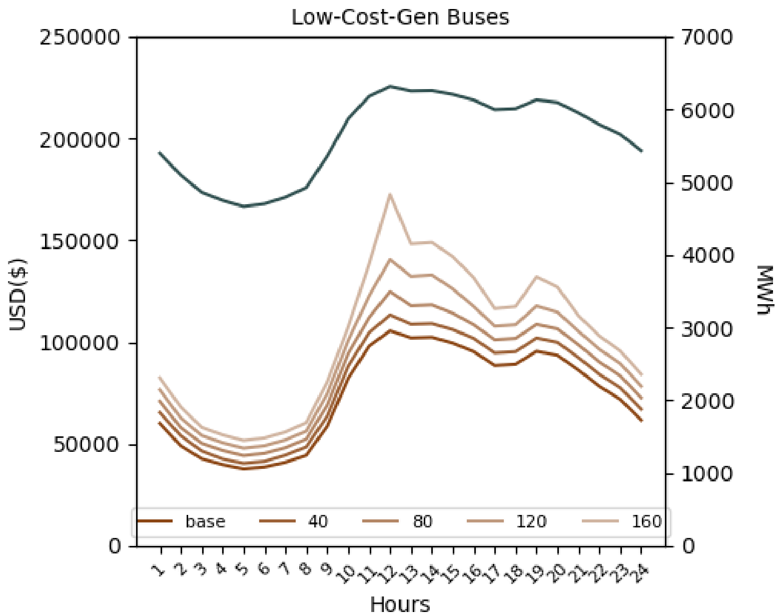

Figure 30: 24-hour cost-to-load of low-cost-gen scenario.

Cost-to-load is up to 63 % higher than the base scenario because of the increase in the LMP around noon due to charging in Figure 30. However, the effect of charging is slighter (44%) during the night-time. Therefore, charging near the low-cost generations at night is better for society than at peak times.

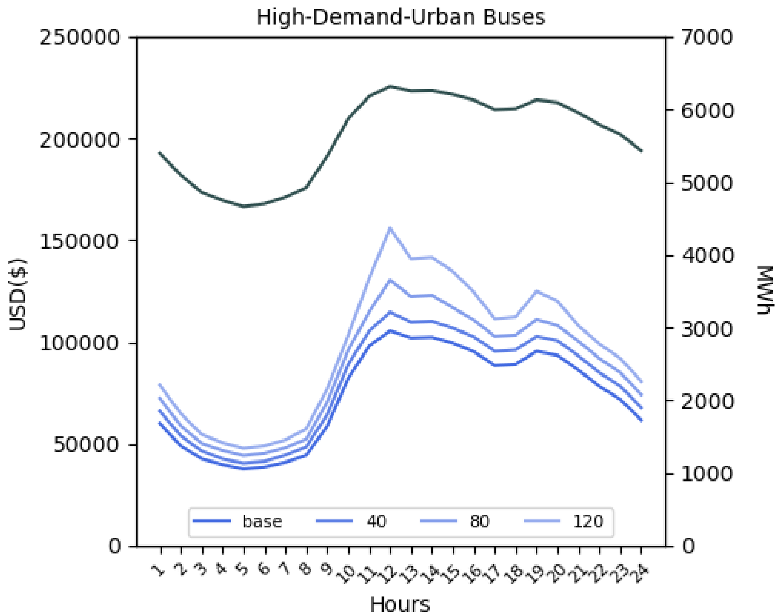

Figure 31: 24-hour cost-to-load of high-demand-urban scenario.

In Figure 31, when the rate of EV is lower, the change of cost-to-load is higher than in all other scenarios. With the addition of EVs to these buses, which already have high demands, it is possible to observe big changes in LMPs even at the smallest percentage of EVs. That's why cost-to-load is increased up to 48% compared to the base scenario for 360kW addition.

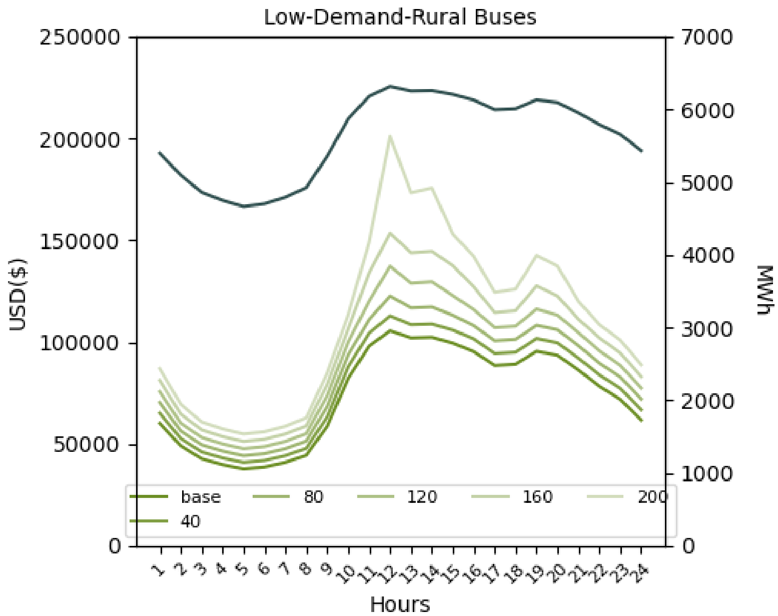

Figure 32: 24-hour cost-to-load of low-demand-rural scenario.

On the contrary, in Figure 32, when the rate of EV is lower, the change of cost-to-load is lower than all other scenarios. In this scenario, where EV is added to buses with low demand, the EV loading rate has a lower cost-to-load change rate (48%) than low-cost-gen scenario (63%) and most-connected complex (71%) for 480 kW addition. Therefore, charging in the low-demanded-rural buses is more desirable for the society than the high-demanded-urban buses.

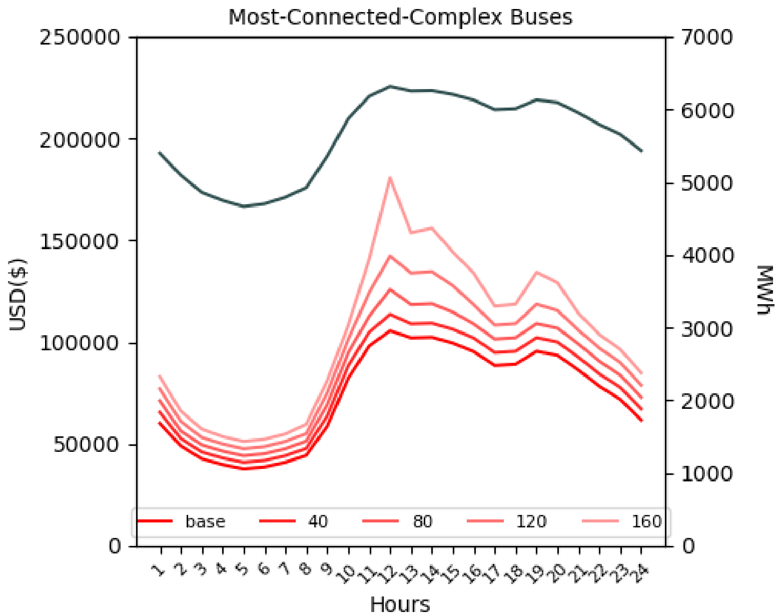

Figure 33: 24-hour cost-to-load of most-connected-complex scenario.

In Figure 33, the buses to which the most lines are connected are selected to add EVs. The changing of cost-to-load depends on the increase of LMPs, which is caused by the congestion of the lines. If more than one line is connected to a bus, that bus can receive the power injected from different points through its multiple lines, meet the demand and reduce the line congestion rate. In fact, even if the demand is low, LMP can rise very high when the line is congested. Determining EVC points according to known infrastructure or identifying lines that may cause congestion according to demand increasing and investing in infrastructure at these points will contribute to the system by reducing cost-to-load in the long term.

Looking at Figures 30, 31, 32, and 33 together, it can be seen that lines are generally different in one scenario from the other. Adding 40 kW to 3 selected buses is equivalent to adding 120 kW to the total demand of 39 buses taken from [86], making the model infeasible after a certain EV% for some scenarios. It is worth repeating that for this study, all network parameters but generation costs are adapted from the original IEEE 39-bus system. The 'a' cost in the cost function is given differently for this paper; however, it was given the same in [86].

So, the model could not be prevented from being infeasible. As seen in Figure 30 and 33, the low-cost-gen buses scenario and most-connected-complex buses scenario turned out to be infeasible after 480 kW, while the high-demand-urban scenario in Figure 31 turned out to be infeasible after 360 kW. Finally, it can be seen in Figure 32 that the low-demand-rural scenario becomes infeasible after 600 kW. Instead of loading EVs on a single bus, by distributing EVs to different buses, the total additional demand can be increased up to 12%. Also, this shows that shifting potential EVC points from complex to lower can reduce the economic impact of EVC on the end-user.

4.2 Implications of EV Charging Loads on Distribution Locational Marginal Prices

This section considers and analyzes the effects of randomized charging of EVs. Driver behavior adaption to the AC and DC charging and battery optimization is also analyzed.

The charging scheme aims to assess the effects of random charge of the EVs in the distribution system on DLMPs. DLMP is used to monitor congestion that the unpredictable behavior of EV owners may cause. In addition to this unexpected behavior of EV owners being an intertemporal problem, considering the flexibility of the drivers, the charging period of EVs should have a multiperiod framework. The methodology steps in Figure 34 are listed below to examine the DLMP differences that may occur when EVs are charged at any time and the DLMP change at that time when the battery is charged because of multiperiod optimization.

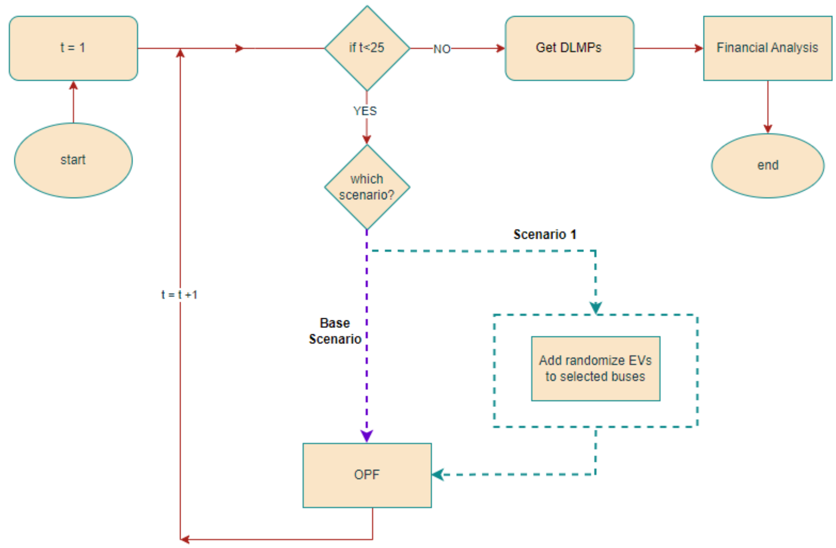

Figure 34: Flowchart of Methodology II.

1. OPF is run for a multiperiod (24 hours) in the base scenario. Each node has a DLMP for every hour, and these prices are used for financial analysis.

2. In the first scenario, 3 EVs were added to buses, which was selected for this scenario in the first place. The multiperiod OPF is performed after these additional loads.

3. The battery optimization step determines the dispatch of the battery according to the base scenario's MCPs. The battery, which optimizes its charging time according to the minimum price in the base scenario, needs more energy than an EV due to round-trip efficiency [88], [89].

After getting DLMPs for all scenarios, the financial analysis is performed based on the cost-to-load term. Since cost-to-load is calculated by multiplying the DLMP of each bus with its demand, it can be called the cost of demand to an end user. Minimizing the cost-to-load by charging the EVs, that is, maximizing social welfare, will be discussed in the following sections.

4.2.1 Test Case 2: IEEE 34-Bus System

The one-line diagram of the modified IEEE 34-bus is shown in Figure 35. Bus number 1 is the reference bus, and it has been assumed that the whole power generation is provided in this bus. Since this is a distribution network, the generator's fixed cost is replaced by hourly MCPs taken from Ref. [90], and they are shown in Figure 36.

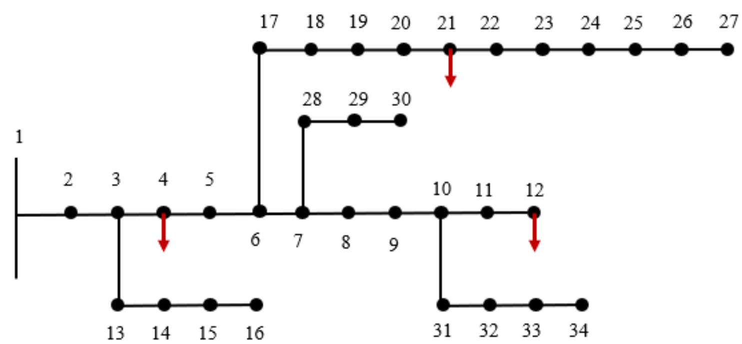

Figure 35: The modified IEEE 34-bus.

There is active demand on every bus except buses 3, 6, 7,10, and the reference bus. The active demands are replaced by residential load profiles taken from the government data site of the United States [91]. Network line capacities or technical settings have remained unchanged in the modified case. The MATLAB platform with a MATPOWER [92] MILP solver simulates five scenarios.

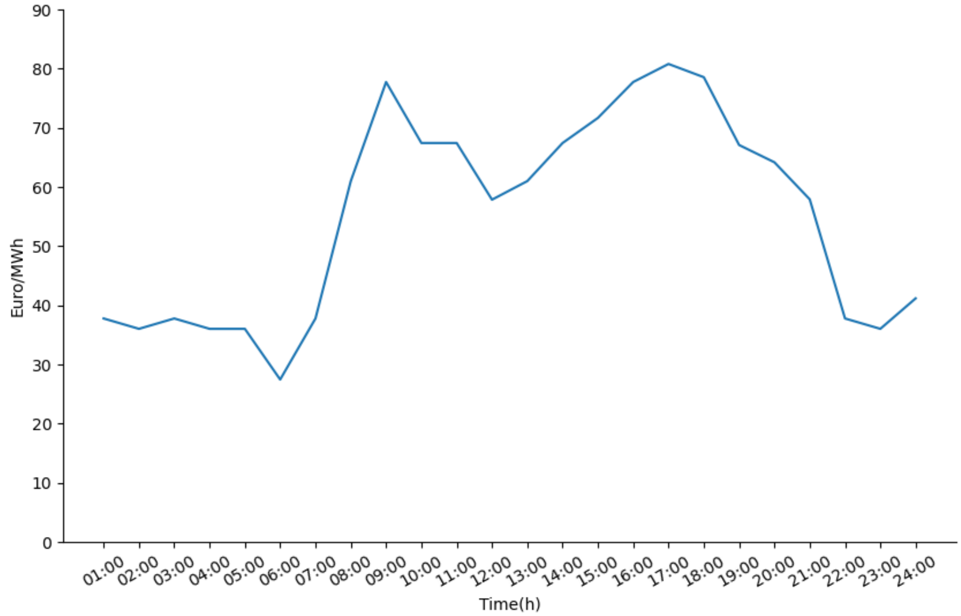

Figure 36: Marginal Clearing Prices for Turkey on Jan 30th 2024.

4.2.2 Case Studies and Results

In this case study, there are the base case, random charging, AC and DC charging, and battery optimization scenarios.

4.2.2.1 Base Case

AC OPF is run for the IEEE 34-bus case with modified demand in the base case scenario. In AC power flow, the losses in the distribution system add to the marginal loss cost in each bus and give a higher value of DLMP. While the losses within 24 hours vary from 10 kW to 20 kW, they go up to 30 kW during peak hours, around 5 pm.

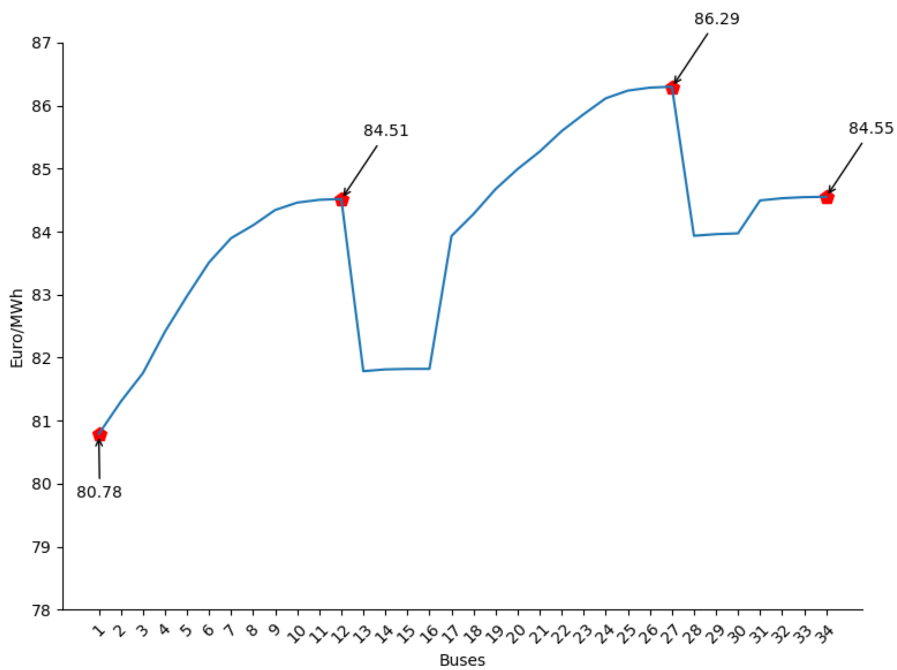

Figure 37: DLMPs for the base scenario at 17:00.

The peak hour of DLMPs for 34 buses is shown in Figure 37. When the DLMPs in Figure 36 are examined, considering the network structure in Figure 35, it is seen that the 27th bus, located at the farthest point of the distribution network, has the highest DLMP, 86.29 Euro/MWh. Since the losses gradually increase as moving to the end of the network, higher DLMPs are seen in the 12th(84.51 Euro/MWh) and 34th(84.55 Euro/MWh) buses compared to the reference bus(80.78 Euro/MWh).

4.2.2.2 Randomize EV Charging Case

It can be seen from the results of the base case that the place of the bus in the distribution network should be considered. For this reason, buses 4, 12, and 21 are selected to add EVCs, which can be seen in Figure 35 with red arrows. Three 120 kW EVCs are added to these buses for 24 hours to create a randomized charging time for this scenario. The additional demand created by not knowing when EVs will be charged increases DLMPs for all hours.

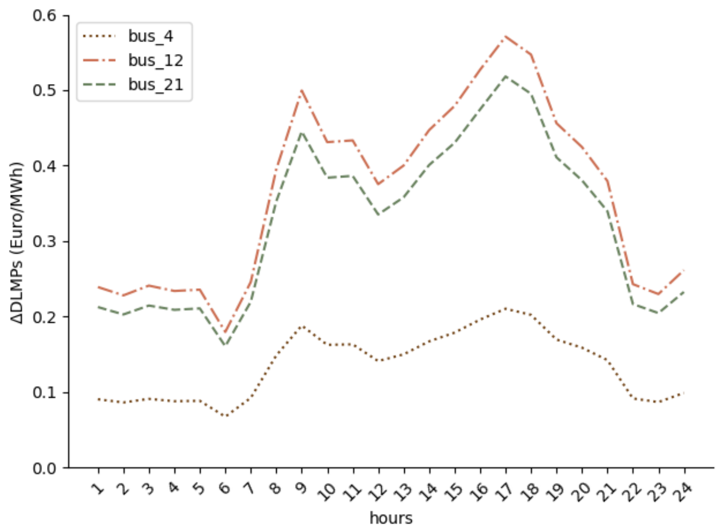

Figure 38: ΔDLMPs for selected buses after adding randomized EVs.

DLMP changes of the selected buses are shown in Figure 38. The minimum DLMP change occurs at 06:00, while the maximum DLMP change occurs at 17:00. Figure 38 shows that bus 12 has the highest increments, especially at the peak. While bus 12 has the highest DLMP change, bus 4 has the lowest DLMP changes. Especially at peak time, the DLMP change in bus 12 compared to the base case is 60 cents, while this value is around 20 cents in bus 4. All three buses show changes in a pattern like the MCPs in Figure 36 over 24 hours, with the most significant change occurring during peak times.

4.2.2.3 AC & DC Charging Cases

In the previous scenario, it was thought EVs would be charged with DC within 1 hour. However, since the driver's behavior is flexible, the EV is assumed to be charged for each hour, considering that this charge will come at any hour. For this reason, temporal analysis of the results is essential. For this subsection, a comparison case study is created for AC and DC charging at the peak hours, which is considered a worst-case scenario to see the highest effect of EVs on DLMPs. DLMP results are obtained for the case of the EV being DC charged within 1 hour only at 17:00 and for the case of the exact vehicle being fully charged between 14:00 and 19:00, which is peak hours in the case of AC charging. DLMP change graphs according to the base case are shown in Figure 39 separately for the three selected buses.

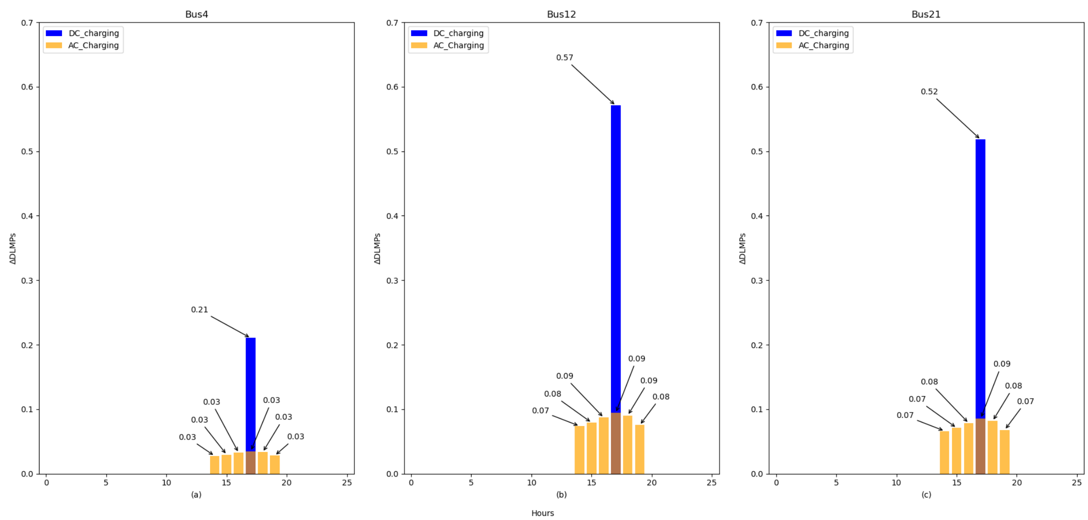

Figure 39: ΔDLMPs for selected buses after AC and DC charging.

In Figure 39(a), DC charging takes 1 hour to charge the vehicle at 17:00, and DLMP is 21 cents. However, AC charging takes 6 hours to fully charge the vehicle and the total DLMP is 18 cents. For buses 12 and 21 in Figure 39(b) and (c), the DLMP changes for 6 hours differ for all hours. For DC, the incremental charging is 57 cents for bus 12 and 51 cents for bus 21. The rest of the hours have the same DLMP with a base scenario for three buses since the EV only charges at peak hours. For the AC charging case, DLMP changes start from 7 cents to 9 cents for Figures 40 (b) and (c). When all daily DLMP changes are examined, AC charging changed by 3 cents less than DC charging for the 4th bus, 7 cents for the 12th bus, and 5 cents for the 21st bus. A financial analysis of the difference between DC and AC charging changes in the DLMP change will be discussed in the next section regarding cost-to-load.

4.2.2.4 *Battery Optimizing Case*

This battery charging scenario is created to mitigate the effects of randomized EVs on DLMPS. In this case, the owner should charge the battery for using the EV driver freely. Again, the battery will be used during peak hours as a DC charger, so the battery should be ready for discharge at this hour. After the battery optimization step, the dispatch of the battery is shown in Figure 40. The red line shows the MCPs.The battery is charged at 06:00, with the minimum MCP. Note that due to the round-trip efficiency of the battery, the new DLMP is higher than the one when the vehicle is charged directly by the DC charging at that hour. However, using battery gives the EV user flexibility for the rest of the day.

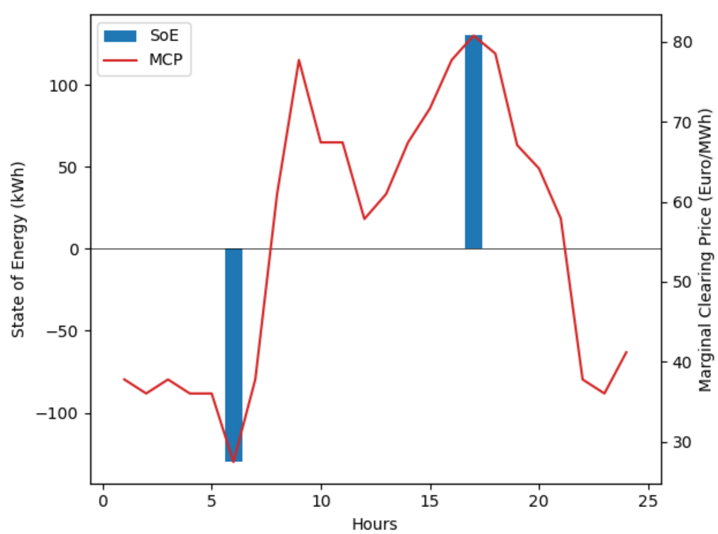

Figure 40: Battery dispatch profile with MCPs of generator.

4.2.3 Discussion

Hourly cost-to-load is obtained by multiplying the DLMP value at each node with the demand at that node for all buses. The 24-hour cost-to-load graph is seen in Figure 41. Since the cost-to-load term is related to the benefit of society, the driver's charging behavior affects everyone on the grid. To prevent the effects of random charging of EVs, this paper analyzes DC and AC charging from the grid and charging from the battery. AC and DC charging of EVs results have been compared to each other with worst case scenarios, which is charging at peak hours. The cost-to-load result of AC charging is lower than the DC charging scenario, even if the green line in Figure 41 is higher than DC charging for most of the peak time. DC charging at 17:00 affects end-users more than any other hour.

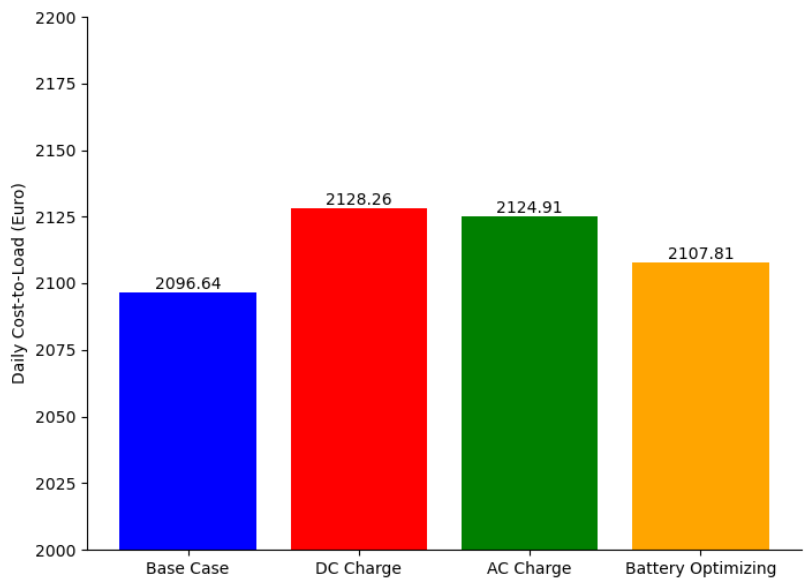

Figure 41: 24 hours-Cost-to-load results for all scenarios.

Although hourly cost-to-load comparison provides a detailed temporal analysis for the considered scenarios, analyzing the scenario results for 24 hours may reveal a different perspective. Daily cost-to-load results in Figure 42 show that DC charging results in an additional cost-to-load of €31.38/day while AC charging costs €28.27/day. However, the battery optimizing case maximizes the social welfare at most by an additional cost of €11.06/day.

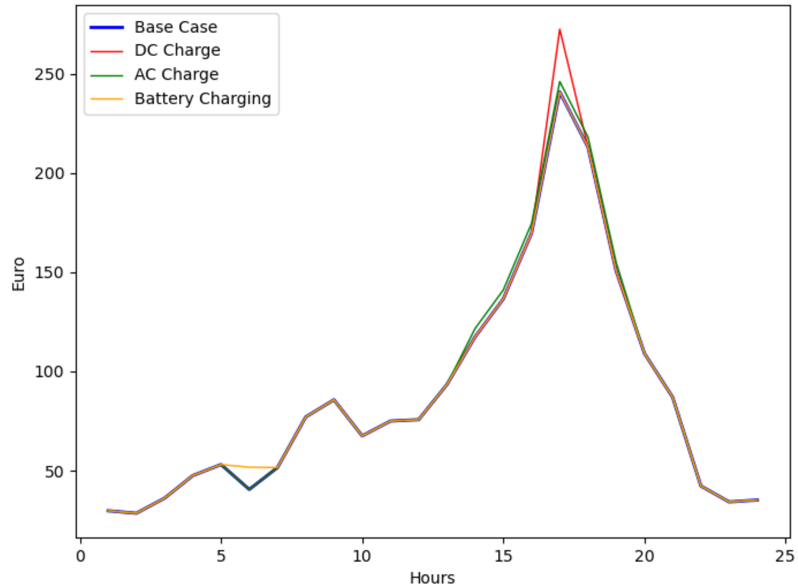

Figure 42: Daily-cost-to-load results for all scenarios.

The success of the battery scenario is promising and will be discussed further. The battery in this study is assumed to be there in the first place with no initial investment. Therefore, one of the critical discussion issues is the ownership of the battery. Should the battery belong to the EV owner or a third-party private organization? Or should EV owners request the state to provide this service? If the EV owner owns to the battery, they want to charge the battery during the cheap hours to offer flexible EV charging to themselves. Moreover, the battery may be used for additional grid services for extra income. Secondly, suppose the third-party private organization owns to the battery; the company may sell energy at a higher price than DLMP for additional profit. Finally, the state owns to the battery; they provide a battery service in a coordinated manner in places where electric vehicles are mainly used.

Further studies by economists, policymakers, and engineers should be supported to discuss the pros and cons of battery ownership options.

CHAPTER V

CONCLUSIONS

The global population's rapid growth has intensified pressure on energy systems, necessitating a transition from fossil fuels to cleaner, renewable energy sources. The intermittent nature of renewable energy necessitates advanced grid infrastructure capable of balancing supply and demand. While electric vehicles offer environmental benefits, their increasing adoption will significantly increase electricity consumption, posing challenges for power grids. Integrating renewable energy and implementing efficient charging strategies are essential for a sustainable energy future.

Electric power systems involve generating electricity from various sources, transmitting it over long distances, and distributing it to consumers. Distribution systems can be configured in different ways, each with its own advantages and challenges. Integrating renewable energy into the grid requires advanced management strategies, with smart grid technology playing a crucial role in optimizing grid operations and facilitating the integration of distributed energy resources.

In power markets, balancing mechanisms are essential for maintaining system stability amid unexpected disruptions or sudden demand spikes. Operators like TEİAŞ manage these imbalances through balancing power markets, utilizing reserves and frequency control to keep the grid's frequency at the standard. Balancing units capable of quickly adjusting production submit bids to this market, and the System Marginal Price is employed to determine costs when there are energy surpluses or deficits. Ancillary services markets ensure the reliable operation of power systems by offering services such as frequency control and reactive power support. In Turkey, the Energy Exchange Istanbul manages the spot electricity market, which comprises the Day-Ahead Market for trading electricity a day before delivery and the Intraday

Market for near real-time trading to address unforeseen imbalances. Pricing methodologies such as marginal, nodal, and zonal pricing are crucial for accurately reflecting electricity costs and optimizing the efficiency of power systems.

EV charging stations are increasingly crucial as the popularity of electric vehicles grows. Charging locations are categorized into 'residential', 'workplace', 'fleet', and 'commercial' stations. 'Residential stations'allow for home charging overnight, 'workplace stations' enable charging during work hours, 'fleet stations' support company vehicles, and 'commercial stations' offer various charging levels in public areas. Turkey has seen significant growth in both the number of electric vehicles and charging points, with projections indicating continued expansion in both areas over the coming decades.

Linear programming (LP) is used to optimize a linear objective function subject to linear constraints, typically framed as minimizing a function subject to a set of equality and non-negativity constraints. The feasible region is defined by linear equations and non-negativity constraints, and solutions are found within this region. Using methods like the Simplex and Barrier techniques, LP solvers efficiently handle various problem formulations and sizes, offering both speed and reliability. These methods iteratively refine solutions for optimal results, whether for minimization or maximization problems.

In power systems, optimization has progressed from early manual calculations to advanced computational techniques. Economic dispatch is a key aspect of power system optimization, focusing on minimizing fuel costs by determining optimal generation levels while adhering to system constraints. It involves unit commitment and real-time dispatch processes, factoring in generator capabilities and transmission limits. The Merit-Order Curve helps rank generators by cost, ensuring that electricity generation matches demand efficiently while maintaining system stability.

The optimal power flow problem minimizes generation costs while meeting constraints on voltage, power outputs, and line flows. This problem is complex due to its nonlinear nature, but simplified models like DC Optimal Power Flow use linear approximations to make it more manageable. Locational Marginal Pricing and Distribution Locational Marginal Pricing extends these concepts to pricing electricity by considering system constraints, losses, and distributed energy resources.

A typical market-clearing model aims to minimize the total generation cost while maintaining power balance, network congestion constraints, and maintaining voltage levels. This model includes constraints for active and reactive power outputs, and it uses the Lagrangian function to derive the distribution locational marginal prices (DLMPs), which reflect the marginal cost of electricity at different nodes. DLMPs differ from traditional locational marginal prices (LMPs) due to distribution network characteristics, including higher power losses, voltage management needs, and potential congestion issues arising from increased distributed energy resources. Accurate DLMP models need to account for these factors and adapt to varying network conditions to reflect operational costs and system value effectively.

This thesis investigates the implications of increased EV load integration on both the transmission and distribution networks, focusing on the impacts on LMP and DLMP. The studies conducted on the IEEE 39-bus and modified IEEE 34-bus systems provide comprehensive insights into the temporal and spatial dynamics of EV charging loads.

The analysis of LMP impacts reveals that the integration of EV loads significantly affects LMPs, particularly during peak demand hours. When EVs are charged near low-cost generators, LMPs increase by approximately 25% compared to the base scenario. Conversely, charging EVs at buses with lower demand results in a less pronounced LMP increase of around 10% during peak hours. Furthermore, rural buses can accommodate more simultaneous EV charging than urban buses, which face limitations due to transmission capacity. The study indicates that relocating EV charging stations from densely populated urban areas to rural locations with lower demand can mitigate the economic impact on end-users by reducing LMP increases.

In the context of DLMPs, the findings emphasize that peak-hour DLMP changes are most pronounced at buses located at the farthest points of the network. In the base case scenario, the farthest bus exhibits the highest DLMP relative to the reference bus, underscoring the importance of considering distribution network losses in DLMP calculations. Randomized EV charging at selected buses results in maximum DLMP changes at the farthest buses, and the comparison between DC and AC charging during peak hours shows that AC charging is more economical. Additionally, nighttime battery optimization offers increased driver flexibility and maximizes social welfare, highlighting the role of batteries in enhancing EV adoption.

These studies collectively offer valuable insights for policymakers, stakeholders, and EV aggregators in navigating the transition toward electrified transportation. By understanding the interactions between EV integration and grid operations at both transmission and distribution levels, effective strategies can be developed to ensure grid reliability and economic efficiency. This thesis contributes to the broader goal of sustainable transportation by providing actionable recommendations to optimize EV charging infrastructure and pricing mechanisms.

APPENDIX

Table 7: Nomenclature for Model 1

Index	
i	Number of nodes
Variables	
P_{gi}	Active power generation at Node i
Q_{gi}	Reactive power generation at Node i
S_{ij}	Complex power on the line connecting Node i and Node j
θ_i	Voltage phase angle at Node i
V_i	Voltage magnitude at Node i
Parameters	
P_{di}	Power demand at Node i
B_{ij}	Susceptance of the line connecting Node i and Node j
G_{ij}	Conductance of the line connecting Node i and Node j
$P_{gi}^{\max}$	Maximum real generation capacity of the generator at Node i
$P_{gi}^{\min}$	Minimum real generation capacity of the generator at Node i
$Q_{gi}^{\max}$	Maximum reactive generation capacity of the generator at Node i
$Q_{gi}^{\min}$	Minimum reactive generation capacity of the generator at Node i
$V_{gi}^{\max}$	Maximum voltage magnitude at Node i
$V_{gi}^{\min}$	Minimum voltage magnitude at Node i
$S_{ij}^{\max}$	Maximum complex power on the line connecting Node i and Node j
f_g	Cost function for electricity production

Table 8: Nomenclature for Model 2

Index	
i	Number of nodes
k	Number of transmission lines
Variables	
P_{gi}	Active power generation at Node i
θ_i	Voltage phase angle at Node i
f_k	Active power flow for line k that connects bus i to bus j
Parameters	
P_{di}	Power demand at Node i
B_{fk}	Susceptance of the line connecting Node i and Node j
$P_{gi}^{\max}$	Maximum real generation capacity of the generator at Node i
$P_{gi}^{\min}$	Minimum real generation capacity of the generator at Node i
$f_k^{\max}$	Maximum real power flow on the line connecting Node i and Node j
f_g	Cost function for electricity production

Table 9: Nomenclature for Model 3

Index	
i	Number of nodes
l	Number of lines
Variables	
P_i^g	Active power generation at Node i
θ_i	Voltage phase angle at Node i
f_k	Active power flow for line k that connects bus i to bus j
λ	Lagrange multipliers associated with active equality power constraints
μ_l^-, μ_l^+	Lagrange multipliers associated with power flow limits
ν_l^-, ν_l^+	Lagrange multipliers associated with active power limits
Parameters	
P_i^d	Power demand at Node i
$T_{(l,i)}$	Power transfer distribution factor of node i to transmission line l
$\overline{P_l}$	Maximum active generation capacity of the generator at Node i
$\underline{P_l}$	Minimum active generation capacity of the generator at Node i
$\overline{F_l}$	Maximum active power flow on the line connecting Node i and Node j
$\underline{F_l}$	Minimum active power flow on the line connecting Node i and Node j
C_i	Cost of generator i

Table 10: Nomenclature for Model 4

Sets	
Ω_L	Set of distribution lines
Ω_N	Set of nodes
Ω_G	Set of generators
Variables	
P_i^G	Active power of generator i
Q_i^G	Reactive power of generator i
P_{loss}	Active power loss
Q_{loss}	Reactive power loss
S_l	Power flow of line l
V_j	Voltage magnitude of bus j
λ^p, λ^q	Lagrange multipliers associated with active/reactive equality power constraints
$\omega_l^{s,\min}, \omega_l^{s,\max}$	Lagrange multipliers associated with power flow limits
$\omega_j^{v,\min}, \omega_l^{v,\max}$	Lagrange multipliers associated with voltage limits
$\omega_l^{p,\min}, \omega_l^{p,\max}$	Lagrange multipliers associated with active power limits
$\omega_l^{q,\min}, \omega_l^{q,\max}$	Lagrange multipliers associated with reactive power limits
κ_i^-, κ_i^+	Lagrange multipliers associated with inequality reactive power constraints
Parameters	
P_i^D	Real power demand at Node i
Q_i^D	Reactive power demand at Node i
$S_l^{\min}, S_l^{\max}$	Minimum / Maximum limits of power flow
$P_i^{G,\min}, P_i^{G,\max}$	Minimum / Maximum limits of active power
$Q_i^{G,\min}, Q_i^{G,\max}$	Minimum / Maximum limits of reactive power
$V^{\min}, V^{\max}$	Minimum / Maximum limits of voltage

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