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MUĞLA SITKI KOÇMAN UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCE

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

ENERGY MANAGEMENT STRATEGIES FOR POWER SYSTEMS WITH RENEWABLE ENERGY SOURCES AND ELECTRIC VEHICLES

MASTER OF SCIENCE (M.Sc.)

MUHAMMED ALİ BEYAZIT

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APPROVAL OF THE THESIS

The thesis submitted by **MUHAMMED ALİ BEYAZIT** with the title of **ENERGY MANAGEMENT STRATEGIES FOR POWER SYSTEMS WITH RENEWABLE ENERGY SOURCES AND ELECTRIC VEHICLES** has been unanimously accepted by the jury members of the 09th of January 2023 to fulfil the requirements for the degree of Master of Science in Electrical and Electronics Engineering Department.

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Muhammed Ali Beyazıt

09/01/2023

ABSTRACT

ENERGY MANAGEMENT STRATEGIES FOR POWER SYSTEMS WITH RENEWABLE ENERGY SOURCES AND ELECTRIC VEHICLES

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Integration of new generation electric loads with high power and energy values, and the continuous increase of renewable energy systems (RESs) penetration in power system has caused significant changes on the system operations. In order to address the operational challenges caused by these changes in power grid, the incorporation of new energy management approaches into power system operation is vital. In this context, energy management approaches such as demand-side management, controlled charging of electric vehicles (EVs) as flexible load and vehicle-to-grid (V2G) technology that enables EVs to be used as a storage unit have been arisen prominent research areas. Therefore, this thesis presents a comprehensive research about the energy management of two different operations which are a neighborhood composed of residential end-users, and mobile charging stations (MCSs) responsible for EV charging.

In the first method, an energy management approach has been proposed for a neighborhood including residential end-users with rooftop photovoltaic (PV) systems, a shared energy storage system (ESS) and an electric vehicle (EV) fleet. The proposed approach presents a novel energy credit mechanism (ECM) for the EV fleet and households separately to exploit the EV batteries and store the excess PV energy in the neighborhood through the shared ESS for later use. End-users gain energy credits before a demand response (DR) event and use these credits during the peak periods to minimize their total energy cost (TEC), resulted in a decrease in the peak demand. Also, the energy credits gained by the EV fleet are used through the vehicle-to-home (V2H) and vehicle-to-grid (V2G) services with the same objective. In order to conduct a more realistic analysis, a battery degradation cost estimation model is employed and the uncertain behavior of the EV users is considered. The case studies show that the proposed optimization strategy has the capability of considerably reducing the energy costs and peak demand.

In the second method, a routing problem-based energy management strategy is proposed considering both the spatial status of EVs and temporal status of the EVs' charging demands for multiple MCSs in a linear programming framework. The main objective of the study is to minimize the charging costs while satisfying the charging requests of EVs, by also taking the daily price tariff into account. The results are validated through various case studies including different numbers of MCSs and wind power as a RES.

Keywords: Demand response, electric vehicles, energy storage systems, microgrid, mobile charging station, vehicle-to-grid

ÖZET

YENİLENEBİLİR ENERJİ KAYNAKLARI VE ELEKTRİKLİ ARAÇLAR İLE GÜÇ SİSTEMLERİ İÇİN ENERJİ YÖNETİM STRATEJİLERİ

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Yüksek güç ve enerji değerlerine sahip yeni nesil elektrik yüklerinin entegrasyonu ve güç sistemindeki yenilenebilir enerji kaynakları sayısının gün geçtikçe artması, sistem işletiminde önemli değişikliklere neden olmuştur. Güç şebekesindeki bu değişikliklerin neden olduğu işletim zorlukların üstesinden gelmek için, yeni enerji yönetimi yaklaşımlarının güç sistemi operasyonuna dahil edilmesi hayati önem taşımaktadır. Bu kapsamda talep tarafı yönetimi, elektrikli araçların esnek yük olarak kontrollü şarj edilmesi ve elektrikli araçların bir depolama birimi olarak kullanılmasını sağlayan araçtan şebekeye enerji aktarım teknolojisi gibi enerji yönetimi yaklaşımları gelecek vaat eden araştırma alanları olarak ortaya çıkmıştır. Bu nedenle, bu tezde konut son kullanıcılarından oluşan bir mahalle ve elektrikli araç şarjından sorumlu mobil şarj istasyonları olmak üzere iki farklı operasyonun enerji yönetimi hakkında kapsamlı bir araştırma yapılmıştır.

Birinci yöntemde, çatı üstü güneş panellerine sahip konut son kullanıcılarından, bir paylaşımlı enerji depolama sisteminden ve elektrikli araç filosundan oluşan bir mahalle için bir enerji yönetim yaklaşımı önerilmiştir. Önerilen yaklaşım, elektrikli araç bataryalarından yararlanmak ve ihtiyaç fazlası güneş enerjisini daha sonra kullanmak üzere paylaşımlı enerji depolama sisteminde depolamak için elektrikli araç filosu ve hanelere ait iki ayrı özgün enerji kredi mekanizması sunmaktadır. Son kullanıcılar, bir talep cevabı etkinliğinden önce enerji kredisi kazanmakta ve bu kredileri toplam enerji maliyetlerini en aza indirmek için pik güç zamanlarında kullanmaktadırlar, bu da pik talepte bir düşüşe neden olmaktadır. Ayrıca, elektrikli araç filosunun kazandığı enerji kredileri de aynı amaç ile araçtan eve ve araçtan şebekeye enerji aktarım servislerinde kullanılmaktadır. Daha gerçekçi bir analiz yapabilmek için, bir batarya bozulma maliyet tahmin modeli kullanılmış ve elektrikli araç kullanıcılarının belirsiz davranışları göz önünde bulundurulmuştur. Durum çalışmaları, önerilen optimizasyon stratejisinin enerji maliyetlerini ve pik talebi önemli ölçüde azaltma yeteneğine sahip olduğunu göstermektedir.

İkinci yöntemde, doğrusal bir programlama çerçevesinde birden fazla mobil şarj istasyonu için elektrikli araçların hem mekânsal durumu hem de elektrikli araç şarj taleplerinin zamansal durumu göz önünde bulundurularak, rotalama problemine dayalı bir enerji yönetimi stratejisi önerilmiştir. Çalışmanın temel amacı, elektrikli araçların şarj taleplerini karşılarken, günlük fiyat tarifesini de dikkate alarak şarj maliyetlerini en aza indirmektir. Sonuçlar, farklı sayıda mobil şarj istasyonu ve bir yenilenebilir enerji kaynağı olarak rüzgâr enerjisini de içeren çeşitli durum çalışmalarıyla doğrulanmıştır.

Anahtar Kelimeler: Araçtan şebekeye enerji teknolojisi, elektrikli araçlar, enerji depolama sistemleri, mikro şebeke, mobil şarj istasyonu, talep cevabı.

To My Precious Family

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C_{labor}	Labor cost to replace the battery.
C_e^{deg}	Degradation cost of the battery in $/kwh for EV e.
$\mathrm{C_{unit}}$	Battery cost in $/kWh.
$D_{i,j}$	Distance between nodes i and j (km).
DoD	Depth of Discharge.
ED_i^{EV}	The energy demand of the EV at node i (kWh).
$E_h^{Crd,0}$	Initial energy credit of house h.
$E_e^{Crd,EV0}$	Initial energy credit of EV e.
$E_h^{Crd,max}$	Energy credit limit of house h.
$E^{tr,unit}$	Unit energy consumption per km during the traveling of MCSs (kWh).
$LD_{h,t}$	Load demand of house h in time period t.
K	Sufficiently large positive integer.
N	Number of MCSs.
N_{cycle}	Battery cycle life.
P_{ESS}^{CH}	ESS charging power limit.
P_{EV}^{CH}	EV charging power limit.
P_{MCS}^{CH}	MCS charging power limit.
P_{ESS}^{DCH}	ESS discharging power limit.
P_{EV}^{DCH}	EV discharging power limit.
P_{MCS}^{DCH}	MCS discharging power limit.
$P_{h,t}^{PV}$	PV power produced by house h in time period t.
P^{TR}	Power limit of the transformer.

PV_h^{cap}	Power production capacity for house h.
$PV^{cap,tot}$	Total PV power production capacity in neighborhood.
$SOE^{ESS,0}$	ESS initial energy level.
$SOE^{ESS,max}$	ESS maximum energy level.
$SOE^{ESS,min}$	ESS minimum energy level.
$SOE_e^{EV,0}$	EV initial energy level.
$SOE_e^{EV,cap}$	EV maximum energy level.
$SOE_e^{EV,min}$	EV minimum energy level.
$SOE^{MCS,cap}$	Maximum SoE level of MCSs.
SV	Salvage value of an EV battery.
T_{arr}	Arrival time of EVs.
$T^{DR,end}$	DR event ending time.
$T^{DR,start}$	DR event starting time.
T^{end}	Ending time of the day.
t_i^{low}	The lower time limit for charging defined by the EV user at node i.
t_i^{up}	The upper time limit for charging defined by the EV user at node i.
$t_{i,j}$	Time spent for traveling between nodes i and j (hour).
ΔT	A certain time period.
γ^{ch}	Allowed charging time limit for MCSs.
λ_t^{buy}	Energy purchasing price.
λ_t^{sell}	Energy selling price.
η^{CH}	Charging efficiency of the ESS, EVs and MCSs.
η^{DCH}	Discharging efficiency of the ESS, EVs and MCSs.
b_t^1	Binary variable (1 or 0 in time period t).
b_t^2	Binary variable (1 or 0 in time period t).

$b_{e,t}^{3}$	Binary variable (1 or 0 in time period t).
$b_{h,e,t}^{4}$	Binary variable (1 or 0 in time period t).
$E_{h,t}^{Crd}$	Energy credit gained by house h in time period t.
$E_{e,t}^{Crd,EV}$	Energy credit gained by EV e in time period t.
$E_{m,i,j}^{tr}$	Total energy consumption of MCS m between i and j during traveling time (kWh).
$E_{m,t}^{tr}$	Total energy consumption of MCS m in time interval t (kWh).
$P_{h,t}^{buy,ESS}$	Power provided from the ESS to the house h in time period t.
$P_{e,t}^{buy,EV}$	Power provided from the EV e to the houses in time period t.
$P_{h,t}^{buy,G}$	Power provided from the grid by house h in time period t.
$P_{h,t}^{buy,L}$	Power provided by the neighborhood to the house h in time period t.
$P_{h,e,t}^{buy,T}$	Total power purchased by house h and EV e in time period t.
$P_{m,i,t}^{ch,MCS}$	Charging power of the MCS m at node i in time interval t (kW).
$P_{m,t}^{ch,MCStot}$	Total charge power of the MCS m in time interval t (kW).
$P_{m,i,t}^{dis,MCS}$	Discharging power of the MCS m at node i in time interval t (kW).
$P_{m,t}^{dis,MCStot}$	Total discharge power of the MCS m in time interval t (kW).
$P_{i}^{dis,MCS}$	Total discharge power in node i (kW).
$P_{t}^{ESS,ch}$	ESS charging power in time period t.
$P_{t}^{ESS,dch}$	ESS discharging power in time period t
$P_{t}^{ESS\rightarrow G}$	ESS power provided to the grid in time period t.
$P_{t}^{ESS\rightarrow N}$	ESS power provided to the neighborhood in time period t.
$P_{e,t}^{EV,ch}$	Charging power of EV e in time period t.
$P_{e,t}^{EV,dch}$	Discharging power of EV e in time period t.
$P_{e,t}^{EV\rightarrow G}$	The power of EV e transferred to the grid in time period t.

$P_{e,t}^{EV\rightarrow N}$	The power of EV e transferred to the neighborhood in time period t.
$P_{t}^{G\rightarrow ESS}$	Total power transferred from grid to ESS in time period t.
$P_{e,t}^{G\rightarrow EV}$	Total power transferred from grid to EV e in time period t.
$P_{t}^{G\rightarrow N}$	Total power drawn from grid to the neighborhood in time period t.
$P_{t}^{G\rightarrow TR}$	Total power purchased from grid via transformer in time period t.
$P_{t}^{N\rightarrow ESS}$	Neighborhood surplus power provided to the ESS in time period t.
$P_{e,t}^{N\rightarrow EV}$	Neighborhood surplus power delivered to EV e in time period t.
$P_{t}^{N\rightarrow G}$	Total power delivered from neighborhood to the grid in time period t.
$P_{h,t}^{PV,used}$	PV power used by house h to satisfy energy demand in time period t.
$P_{h,t}^{sell,ESS}$	Power provided by house h to the ESS in time period t.
$P_{e,t}^{sell,EV}$	Power provided by houses to the EV e in time period t.
$P_{h,t}^{sell,G}$	Power provided by the house h to the grid in time period t.
$P_{h,t}^{sell,L}$	Power provided by house h to the neighborhood in time period t.
$P_{h,e,t}^{sell,T}$	Total power sold by house h and EV e in time period t.
$P_{t}^{TR\rightarrow G}$	Total power transferred to the grid via transformer in time period t.
SOE_{t}^{ESS}	Energy level of the ESS in time period t.
$SOE_{e,t}^{EV}$	Energy level the EV e in time period t.
$SOE_{m,t}^{MCS}$	Energy level the MCS m in time period t.
$T_{m,i}^{ch,tot}$	Total charging period of MCS m in node i (hour).
$T_{m,i}^{dis,tot}$	Total discharging period of MCS m in node i (hour).
$\tau_{m,i}^{end,ch}$	Ending time of charging operation for MCS m in node i.
$\tau_{m,i}^{end,dis}$	Ending time of discharging operation for MCS m in node i.
$\tau_{m,i}^{start,ch}$	Starting time of charging operation for MCS m in node i.
$\tau_{m,i}^{start,dis}$	Starting time of discharging operation for MCS m in node i.

$x_{m,i,j}$	Binary variable for the travel phase of MCSs. $x_{m,i,j}$ denotes whether path (i,j) is traveled by MCS m.
σ	Battery capacity in kWh.
CC	Capital Cost
DLC	Direct Load Control
DR	Demand Response
ECM	Energy Credit Mechanism
ESS	Energy Storage System
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
EVPL	Electric Vehicle Parking Load
GAMS	General Algebraic Modeling System
IEA	International Energy Agency
LSE	Load Serving Entity
MCS	Mobile Charging Station
PLR	Peak Load Reduction
PV	Photovoltaic
RESs	Renewable Energy Systems
SoE	State of Energy
TEC	Total Energy Cost
V2H	Vehicle-to-Home
V2G	Vehicle-to-Grid
WT	Wind Turbine

1. INTRODUCTION

1.1 Objective of the Thesis

The electricity sector has undergone substantial changes in the 21st century that have an impact on both demand and supply sides of electricity networks in the light of sustainable and climate-friendly investments (Çiçek et al. 2021; Mohseni et al. 2022). In particular, the transportation sector has drawn attention because of its high carbon emission rate and its potential to promote environmentally and socially sustainable goals of many countries (Hussain et al., 2022).

As a consequence of policies and in response to technological developments and growing market in the recent years, electric vehicles (EVs) have grown in popularity significantly. The sales of EVs topped 6.6 million globally and the EV registration increased by 75%, in the first quarter, from the same period in 2021 according to the International Energy Agency (IEA) (Anonym, 2022).

At the same time, the electricity-production industry is undergoing a major transformation from fossil fuels to non-polluting renewable energy systems (RESs), due to the increasing cost of fossil fuels, the depletion of fossil sources, and the increase in environmental consciousness (Mohseni et al., 2022). Besides, the increasing penetration of non-dispatchable RESs like wind turbines (WTs) and photovoltaic systems (PVs) may pose serious challenges to the stability of the entire power grid because of their highly variable nature (Garlet et al. 2019; Hussain et al. 2021).

To address these issues, the microgrid concept emerged as an efficient way to promote widespread adoption of RESs, reduce grid congestion on existing lines and increase overall grid capacity (Dagar et al., 2021). Microgrid can be defined as a complex energy system that includes several smart grid functions such as distributed generation, digital and two-way communication, adaptive and islanding mode, and autonomous and coordinated control (Nasser et al. 2021; Saeed et al. 2021).

Besides, microgrids provide an effective solution to the issues related to the large-scale integration of flexible loads such as EVs. However, additional EV charging demand can lead in active power losses and congestion in power grid, which could subsequently result in equipment failure or degradation due to overloading of transformers or power lines (Venegas et al., 2021). In addition to these grid limitations, EV charging may cause technical challenges to load serving entity (LSE) such as voltage drops and phase-unbalances.

To overcome these issues, demand response (DR) programs, that offer an important source of flexibility, have been proposed in the literature. Demand management strategies are considered to be an effective tool for minimizing the effects of future uncertainty. Besides, DR programs offers a better solution in a microgrid with energy storage systems (ESSs) and vehicle-to-grid (V2G) technology.

The ESSs are paramount in the microgrids because they ensure the balance between energy production and consumption especially when using with RESs that have intermittent and highly variable nature (Ouramdane et al., 2021). This encourages some non-critical loads to be shifted from peak to off-peak energy demand periods.

On the other hand, EVs have the opportunity to become not only vehicles, but also a flexible demand source, and mobile energy storage units with V2G technology (Sovacool et al., 2020). Therefore, V2G technology is regarded as one of the most promising smart grid concepts, particularly due to the fact that EVs have large batteries and are idle for most part of the day (Latifi et al. 2021; Yoo et al. 2021; Brancaccio et al. 2022). In the case of distribution grids, V2G technology can improve the power system reliability and efficiency, and defer costly infrastructure reinforcements.

However, finding suitable charging station, waiting time in the charging stations and overloading on the power grid are still the most important challenges for both EV users and LSEs. The ratio of EVs per charger has increased between 2010 and 2021 in the world according to IEA (Anonym, 2022). Therefore, EV charging may still cause to overloading on the power grid due to the similar charging behaviors of EV users even though, the DR program and microgrid approaches offer remarkable solutions for EV charging.

Recent studies in the area of charging infrastructures are predominantly focused on new EV charging techniques such as mobile charging stations (MCSs) to overcome aforementioned issues. MCS can be defined as an autonomous truck, which carries a high capacity battery pack, a control unit and a charger plug. The charge of EVs with MCS in a certain location and time period, determined by the EV users, have a potential to increase the participation of EVs into DR programs and V2G services, while to remove the challenges for both EV users and LSE.

Eventually, two novel energy management techniques have been developed in this thesis, detailed in section 3, in separate power grid environments and with different system components to prevent overloading in the power system and provide economic benefits to end users or LSE.

2. LITERATURE REVIEW

2.1 Cost Optimization of A Microgrid Considering Vehicle-To-Grid Technology and Demand Response

In order to address the operational challenges caused by significant changes of power grids, the incorporation of DR programs into power system operation has become more essential in the recent decade. The DR programs that benefit from energy-saving capabilities of flexible loads such as thermostatically controllable loads and EVs have been discussed in the literature as a cost-effective solution. The main target of these studies was to maintain the flexibility and reliability of power grid and to ensure that the residential end-users satisfy their energy demands on their own.

In (Güner et al., 2020), a mathematical model that aims to increase the distribution system reliability for a system structure involving on-site PV units and DR strategies was proposed. Song et al. (2018) examined the effects of dynamic price-based DR application on the system reliability by considering the nodal price uncertainties and potential flexibility without RES-based production. A security constraint unit commitment model was presented in (Ribeiro et al., 2017) by integrating a DR program and considering RESs where the system was modeled via a multi-objective problem by considering the market efficiency, system reliability and air pollution.

Yu et al. (2022) studied on the smart homes participated in a DR program and developed a smart home integrated management model based on a non-dominated sorting genetic algorithm to reduce the peak load and electricity costs. To evaluate the influence of smart homes on the distribution grid, several electricity appliances were involved in the study by considering different types of householder behaviors. Furthermore, the regions with and without a time-of-use tariff were compared, demonstrating that the time-of-use tariff outperforms the no-time-of-use tariff.

In a similar study, a direct load control (DLC) approach was presented to improve the power system operations in terms of willingness of end users to participate in the DLC-based DR program (Erdinç et al., 2019). To increase the participation of the end users of residential heating, ventilation and air conditioning units, an incentive mechanism based on providing energy credits was used. However, the RES-based production was not included in studies (Erdinç et al. 2019; Yu et al. 2022) and ESSs were not considered in studies (Ribeiro et al. 2017; Song et al. 2018; Erdinç et al. 2019; Güner et al. 2020; Yu et al. 2022).

In (Sengor et al., 2019) and (Sengor et al., 2021), an optimal energy management model for an EV parking lot (EVPL) was proposed by considering the peak load reduction (PLR)-based DR programs to enhance the power system flexibility and maximize the load factor of EVPL. The uncertain behavior of EVs was also taken into account by considering the real historical data. Nevertheless, the RES-based production and ESSs were not investigated in both studies.

The applicability and efficiency of the DR programs can be improved to a greater extent when they are implemented within a microgrid that includes ESSs. Furthermore, the large-scale energy storage units have been widely regarded as one of the most effective backup assets for the power system operations, especially when using with RESs that have intermittent and nondispatchable nature. None of the aforementioned studies, however, has considered these large-capacity ESSs.

In (Walker and Kwon, 2021), a shared energy storage control policy was developed based on the real historical data to reduce the cost of the electricity cost for residential consumers while taking into account the stochastic nature of load demand, PV power production and real time electricity price. An energy management approach was developed in (Torreglosa et al., 2016) for controlling the energy exchanges between the PV generation, ESS and EV charging station (EVCS). However, the DR programs and V2G/Vehicle-to-Home (V2H) services were not taken into account in both studies.

Chamandoust et al. (2020) offered a multi-objective scheduling problem for a smart microgrid including WT, diesel generators and ESSs, and studied on the service pricing and load scheduling with the aims of minimizing the operation cost, carbon emission, load curtailment cost and deviation between the power generation of WTs and demand profile.

A stochastic energy management framework for a microgrid consisting of PV systems and ESS was proposed in (Prudhviraj et al., 2020) to minimize the energy cost. A 15-node radial distribution network was used in the study to evaluate the stochastic energy management framework, which was formulated as mixed integer non-linear programming. As a result, the comparative case studies validated the effectiveness of the DR strategy and ESS as a cost-effective solution. Besides, a detailed comparison analysis based on RESs, diesel generator and ESSs was conducted in (Murty and Kumar, 2020) by taking a DR program into account to determine the optimum capacity and techno-economic benefits of a standalone microgrid. The simulation results showed that PV plus ESS is the most economical configuration.

In (Taşcıkaraoğlu, 2018), an energy management strategy for a residential area including RESs and detached houses was discussed by using an energy credit based-DR program with a shared ESS. An optimization problem was developed to minimize the energy costs of end users and reduce the peak demand in a dynamic price environment. Nevertheless, none of the aforementioned studies has considered the V2G/V2H services.

In addition to the ESSs, the potential of the EVs as energy storage units was also investigated in the recent literature by making use of the V2G technology that enables the bidirectional power flow between the EV battery and power grid (Honarmand et al., 2014). This technology enables EVs to be used as both a flexible demand source and a storage option in smart grids (van der Kam and van Sark, 2015). In the literature, many technical and economic studies have been carried out to ensure the flexibility and reliability of the power system by using the V2G and V2H services.

In (Bibak and Tekiner-Mogulkoc, 2022), a performance evaluation method was proposed to show the impacts of EVs and V2G service on reducing the peak demand

and filling the valley demand at varying penetration levels of EVs and V2G service. According to the case studies, the analyses indicated that charging EVs at late night or early morning would be best option for PLR. However, the effects of EV charging and V2G service were not investigated by using the DR programs and the EV battery degradation was not addressed.

Tiwari et al. (2020) presented a distributed resource allocation approach with a large number of plug-in EV connected to a microgrid considering the charging/discharging patterns. The main purpose of this study was the load profile smoothening and minimizing of load shifting; however, DR programs and any battery degradation model were not handled in this study.

A flexibility evaluation method for distribution systems was propounded in (Liu, 2020), which is based on RESs and charging/discharging control strategy of EVs. In the study, the battery capacity, driving plan of EV and traffic network were modeled; however, neither DR programs nor battery degradation model were examined.

In (David and Al-Anbagi, 2017; Amamra and Marco, 2019; Abdelaal et al. 2021; Wu and Lin, 2021; Huang et al. 2022), the potential benefits of the V2G and V2H services were investigated by considering the battery degradation of EVs.

Wu and Lin (2021) presented an electricity supply cost model to reduce the total electricity cost by integrating the EVs into the power system in China and investigated the load demand and electric supply cost for each of the three charging modes: uncontrolled charging, controlled charging, and V2G charging. Since the analysis is based on the existing fixed tariff in China, neither DR strategies nor real-time tariffs were not taken into account. The use of the V2G service has provided a relative profit in the fixed tariff environment along with the battery degradation cost.

David and Al-Anbagi (2017), Amamra and Marco (2019) presented bidirectional V2G operation methods to provide the frequency regulation service while in (Abdelaal et al., 2021) a home energy management system was proposed by using the EV batteries. In the three studies above, the technical and economic benefits on the power system were assessed using only three different EV data and in terms of only the bidirectional V2G/V2H services. Thus, RES-based production, ESSs and DR-based programs were not taken into account.

Huang et al. (2022) suggested a model in which EVs are charged at home in the evening and power is delivered to the grid via V2G service at the workplace during the day with the aim of peak shaving and valley filling. The economic and environmental benefits of a city-scaled V2G model were analyzed while including battery degradation but not DR strategies.

Table 2.1 presents a comprehensive comparison of the recent studies in this area to show the main contributions of this study. As seen from the table, this study differs significantly from the existing literature, particularly in that it considers both the energy credit mechanism (ECM) and EV charging/discharging using V2G/V2H technologies with battery degradation (Beyazıt et al., 2022). Unlike the previous studies, the ECM has been modified to serve a microgrid that comprises a shared ESS, an EV fleet and rooftop PV systems. Due to the uncertain behavior of the EV drivers and the different charge/discharge characteristics of EVs from residential loads, two separate ECMs have been developed, one for the shared ESS and one for the EV fleet.

Table 2.1. Taxonomy of the proposed method compared to similar studies.

Ref.	DR strategy	Time-Varying Price	ECM	RES-based production		Large-Scale ESS	EV Charging Cost	V2G/ V2H	Battery Degradation	Point of view	
				PV	WT					LSE	End-user
Güner et al. (2020)	✓	-	-	✓	-	-	-	-	-	✓	✓
Song et al. (2018)	✓	✓	-	-	-	-	-	-	-	✓	✓
Ribeiro et al. (2017)	✓	✓	-	-	✓	-	-	-	-	✓	-
Yu et al. (2022)	✓	✓	-	-	-	-	-	-	-	✓	✓
Erdinç et al. (2019)	✓	✓	✓	-	-	-	-	-	-	✓	✓
Sengor et al. (2021)	✓	-	-	-	-	-	✓	-	-	✓	-
Sengor et al. (2019)	✓	-	-	-	-	-	✓	-	-	✓	✓
Walker and Kwon (2021)	-	✓	-	✓	-	✓	-	-	-	-	✓
Torreglosa et al. (2016)	-	-	-	✓	-	✓	✓	-	-	✓	-
Chamandoust et al. (2020)	✓	✓	-	-	✓	✓	-	-	-	-	✓
Prudhviraj et al. (2020)	✓	✓	-	✓	-	✓	-	-	-	✓	-
Murty and Kumar (2020)	✓	✓	-	✓	✓	✓	-	-	-	✓	-
Taşcıkaraoğlu (2018)	✓	✓	✓	✓	-	✓	-	-	-	✓	✓
Bibak and Mogulkoc (2022)	-	-	-	-	-	-	✓	✓	-	✓	-
Tiwari et al. (2020)	-	-	-	-	-	-	✓	✓	-	✓	✓
Liu (2020)	-	-	-	✓	-	✓	✓	✓	-	✓	-
Wu and Lin (2021)	-	-	-	-	-	-	✓	✓	✓	✓	-
David and Al-Anbagi (2017)	-	✓	-	-	-	-	-	✓	✓	✓	✓
Amamra and Marco (2019)	-	-	-	-	-	-	✓	✓	✓	✓	✓
Abdelaal et al. (2021)	-	✓	-	-	-	-	✓	✓	✓	✓	✓
Huang et al. (2022)	-	✓	-	✓	✓	-	✓	✓	✓	✓	✓
Beyazit et al. (2022) (This study)	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	✓

2.2 Optimal Management of Mobile Charging Stations in Urban Areas in A Distribution Network

The global concerns on the environment such as the climate change and air pollution have been increasing at the last decades due especially to the impacts of fossil fuels. Nevertheless, a significant portion of the energy required for the transportation sector elements including the private vehicles, public transport fleets and trucks is provided by the fossil fuels. As in many sectors, substantial changes are required in the transportation sector to reduce greenhouse gas emissions in the light of sustainable development goals (Erdinç, 2021). To achieve this goal, the integration of electric vehicles (EVs) into transportation and power system play a vital role. Considering the whole lifetime of the vehicles, EVs offer lower tail pipe emissions than internal combustion engine vehicles, which lead to reducing urban air pollution (Metais et al., 2022).

Despite the potential environmental benefits, increasing more interest in EVs has caused to several challenges for EV users. Availability of a suitable charging station, battery charging time and cost of the electricity can be regarded as among the most significant obstacles (Saboori et al., 2021). Considering that majority of the EV drivers have similar driving and charging routines, finding a suitable charging station remains a significant difficulty especially the fact that the ratio of EVs per charging stations is increasing. Furthermore, the large-scale EV charging power will have a significant impact on the power system operations because of the introduced unpredictability and flexibility of the EV charging load (Xiang et al., 2019). The original peak load demand of the power system will increase as a result of the high penetration of EVs, resulting in a rise in the electricity cost for EV charging in a dynamic price environment.

Studies on electric vehicle charging stations (EVCS) have risen to prominence in recent years in order to reduce charging times and operating costs. In this context, many studies have been conducted to assess where the EVCSs should be located, taking into account the structure of the distribution network, the cost of purchasing or renting land, the electricity consumption profiles of consumers in the same region, the routine routes of EVs, and the estimated waiting times of the EVs in the station. Graber et al. (2019) proposed a stochastic optimization problem in order to determine the optimal sizing of EVCSs in an urban area. The focus of the research was to reduce the parking area's investment costs and ensure high Quality of Service levels for EV users. Zhou et al. (2020) addressed and solved the same problem for fast-charging stations by considering the uncertainty of charging demand. Pan et al. (2020) and Sun et al. (2020) aimed to determine the most optimal locations for charging stations by considering EV owners' travel behaviors. In addition, they proposed a coverage location model for EV charging stations to minimize the number of trips missed.

A genetic-based optimization problem was defined in (Huang and Kockelman, 2020) for determining the most suitable charging station sites, taking into account congestion on the roads and charging stations, as well as the demands of EV users. Also, the design details of the chargers at each station were modelled to minimize the operating costs. On the other hand, Luo et al. (2020) and Das et al. (2021) aimed to develop an optimal approach to operate EVCSs in the case that the locations of EVCSs are known.

Luo et al. (2020) proposed a planning strategy based on weighting and taking into account the user demands, the traffic flow, the number of EVs in the EVCS and the charging demand. A charging station management approach that aimed to minimize charging station costs, extend battery life, and prevent effects on the grid while satisfying the demands of vehicle owners was given in (Das et al., 2021).

The literature examples given prove that EVCSs that are properly located and have a sufficient number of charging units can alleviate the existing EV charging challenges by using an effective management strategy. However, fixed charging stations have failed to address the difficulties such as the high cost of land, especially in big cities, and wasting time and energy on roads to get to the EVCS. Besides, the excessive waiting time of EV owners in these stations, even for the optimal operating conditions where the fast and ultrafast charging stations are used is another challenge that the fixed charging stations are facing.

Another method, which has the potential to minimize the technical and economic problems of EV charging times and charging infrastructure, but has been examined in few studies in the literature, is the use of mobile charging stations (MCSs). Saboori and Jadid (2021) presented a mathematical model to integrate the mobile battery energy storage system (MBESS) into distribution network. To operate MBESS and the self-powered electric truck used to transport the entire battery system, a spatial-temporal operation model was developed. An optimization problem was also proposed to minimize the daily operation cost, which was solved using Mixed Integer Linear Programming (MILP). The main goal was to reduce peak demand and power losses on the system as well as the power grid's daily operating costs.

Besides, Cui et al. (2020) offered a mobile charging strategy for EVs that was designed from the perspective of system operator. In addition, through a booking reservation service, this strategy, which was considered as an alternative to fixed charging stations, aimed to provide flexibility and comfort to EV drivers. In the study, they aimed to maximize total service profits by using MILP model while taking into account the cost of using mobile charging vehicles and penalties due to the SO's selectivity.

MCSs for crowded urban areas, and a mathematical model based on the consumer convenience and expense were proposed in (Zhang et al., 2020). A comparative economic analysis of the proposed system and fixed charging station was carried out considering the levelized cost of electricity together with the land and equipment costs.

Jeon and Choi (2021) proposed a framework covering MCSs and fixed charging stations, and considered the actual power system operations including active/reactive power consumption, reactive power capacity of MCS and voltage quality in power system. They aimed to reduce the number of EVs waiting in queue using the truck-mounted MCSs. The optimization algorithm solved by using MILP performed the road routing scheduling of the MCSs and, the charging and discharging scheduling of the MCS. In a similar vein, Saboori et al. (2021) presented a method for modeling and management of MCS to avoid EV queue accumulation and benefit from difference in daily price tariff. The IEEE 33 bus distribution test system with renewable energy sources was employed in the study, and an optimization method was developed to reduce the total daily operation cost and determine the most appropriate route for truck-mounted MCS.

A dynamic vehicle routing problem and an online operating system have been developed in (Tang et al., 2020). Surrogate-based optimization algorithm was used to determine the optimum number, capacity and location of MCSs in case of using multiple MCSs.

Raboaca et al. (2020) developed a nonlinear optimization problem to determine optimal temporary stations based on charging demand in different locations. They showed the comparative results of moving and temporary location operational modes in terms of miss ratio, response time and queuing time. In (El-fedany et al., 2021), a smart coordination system including both MCSs and FCSs was proposed to plan the electric vehicle charging demands. The authors aimed to minimize the waiting times of the EVs in stations, and time and energy to be spent to reach stations.

2.3 The Contributions of the Thesis

In this thesis, two novel energy management models are developed in a linear programming framework by using RESs, a shared ESS, EVs and MCSs with the aim of providing the flexibility and reliability to the power system operation and also economic benefits to the end-users or LSE. Thus, both energy management methodologies (Cost Optimization of A Microgrid Considering Vehicle-to-Grid Technology and Demand Response and Optimal Management of Mobile Charging Stations in Urban Areas in A Distribution Network) consist of optimization problems based on the idea of minimizing energy costs of the end-users and LSE, respectively. Optimization problems developed within the linear programming framework are solved using General Algebraic Modeling System (GAMS) v.25.1.3 software and solver CPLEX.

2.3.1 The contributions of the first method

In the first method, an optimization algorithm including ECM and PLR-based DR program is proposed in a microgrid environment to minimize the energy cost of the end-users and decrease the peak load demand in the power system.

The contributions of the first method are as follows:

- An energy management strategy based on a shared ESS and V2G/V2H services is propounded to serve a grid-connected neighborhood including residential end-users with rooftop PV systems and EVs.

- Novel ECMs have been developed separately for the shared ESS and V2G/V2H services to allocate the benefits from these services fairly.
- The uncertainties belonging to the EV users, which are the unpredictable departure/arrival times and initial state-of-energy (SoE) of EVs, are derived randomly using Weibull distribution and normal distribution method, respectively. Also, the DR event and V2G/V2H services start at certain time steps with regard to the last arrival time of the EVs to maintain the fairness between the end-users.
- A realistic battery degradation cost estimation model is proposed by considering the salvage value contrary to the studies in the literature.

2.3.2 The contributions of the second method

In the second method, a spatial-temporal energy management model based on multiple MCS routing problem with time window is developed in a linear programming framework. It is aimed that to satisfy the charging requests of EVs at the minimum total cost, taking into account the daily price tariff in an urban area.

The contributions of the second method are as follows:

- To deal with the drawbacks of fixed charging stations, a novel mobile charging system is proposed, which enables optimal EV charging at any time and location.
- A spatial-temporal energy management model is developed using MILP to optimize the total daily operation cost of MCSs by linearizing both energy and time dependent routing problem.
- In order to evaluate the effectiveness of the proposed system in a broader perspective, wind power plant data is integrated into the system, and results are studied through case studies.

3. MATERIALS AND METHODS

3.1 Cost Optimization of A Microgrid Considering Vehicle-to-Grid Technology and Demand Response

3.1.1 System description and mathematical model

In this study, a grid-connected microgrid including a neighborhood composed of residential end-users with rooftop PV systems, an EV fleet, an EVCS with V2G/V2H technology and a large-capacity ESS is considered, as shown in Figure 3.1. It can be seen from the system scheme that three different power exchanges are available in the microgrid: between the houses and grid/neighborhood, between the shared ESS and grid/neighborhood, and between the EV fleet and grid/neighborhood. The houses provide their energy demand primarily from their PV systems while the residual demand can be provided from the surplus PV power of the other houses (which will be referred to local power hereafter). When the PV power is insufficient to satisfy all the required demands, additional power may be purchased from the grid or drawn from the shared ESS and EV fleet. On the contrary, the excess PV production, if any, can be sold to the grid or delivered to the shared ESS. In a typical moment, the decision of whether purchasing or selling energy will be made by the energy management system depending on various parameters such as EV departure/arrival times, energy credits and dynamic prices. Also, the neighborhood transformer is assumed to have a load tracking system that prevents the overloading on the transformer windings so that may help to decelerate the aging process.

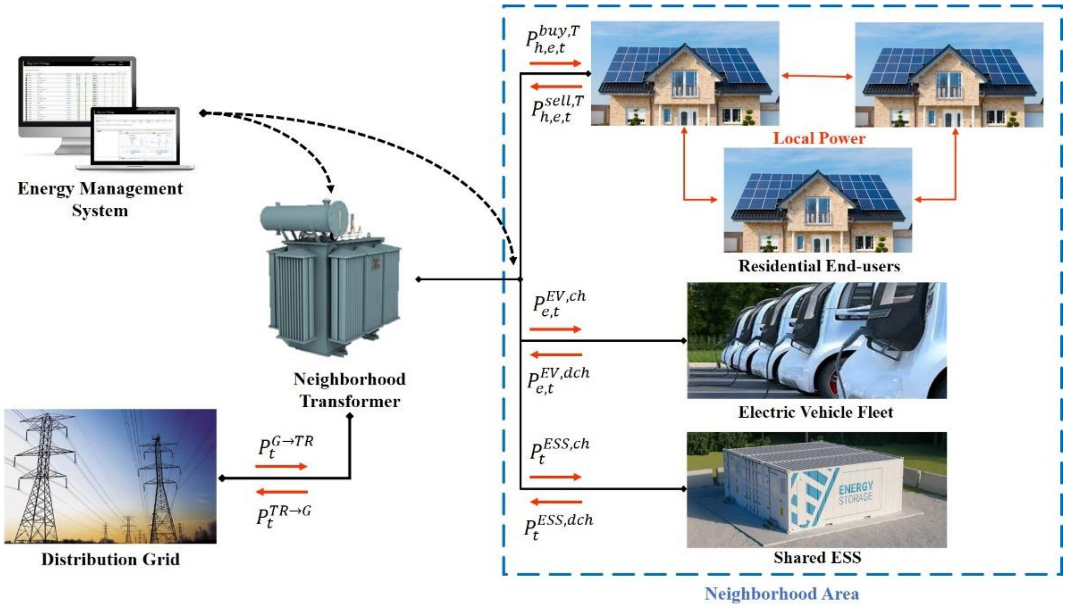

Figure 3.1. The schematic diagram of the system proposed.

3.1.1.1 Battery degradation

In this study, the cost of delivering electricity from an EV to the power grid or to the houses by V2G and V2H services is determined by estimating the battery degradation. Also, when calculating the degradation, the capital cost (CC) of the battery is taken into account, together with the salvage value of the battery once it has run its course. The battery degradation cost of an EV is defined in (2.1) (Abdelaal et al. 2021; Farzin et al. 2016):

$$C_e^{deg} = \frac{(C_{unit} \times \sigma) + C_{labor} - SV}{N_{cycle} \times \sigma \times DoD} \tag{2.1}$$

A deep discharge (*DoD*) is typically suggested as 80% for li-ion batteries (David and Al-Anbagi, 2017). In addition, the cycle life of a battery (*N*), which is for a specific *DoD*, is a measurement of how many charge-discharge cycles the battery can withstand before losing its capacity. C_{unit} and C_{labor} are taken as 137 \$/kWh and \$168 (Abdelaal et al. 2021) while C_{unit}, C_{labor} and σ represent the battery cost per kWh, battery replacement labor cost and EV battery capacity, respectively. Thus, CC is equal to $C_{unit} \times \sigma$. *N* is 3221 cycles at 80% *DoD* as reported in (Han et al., 2019). The salvage value of the battery is denoted by SV in (2.1), which is adapted from (Kolawole and Al-Anbagi, 2019) as equal to 60% of the CC. Hence, the battery degradation cost per kWh varies according to the EV battery capacities given in Table 3.1 and is estimated as an average of $0.0225. As a result, it is taken into account in the objective function of the proposed optimization problem while calculating the total energy cost of the households (TEC).

Table 3.1. Electrical characteristics of electric vehicles

EV Type	Battery Cap. [kWh]	EV Type	Battery Cap. [kWh]
BMW i-3	37.9	Tesla Model 3	75
Hyundai Kona	64	Kia E-Niro	64
Mini Cooper Se	28.9	Audi Q4 E-Tron	76.6
Mercedes Eqc 4matic	80	Hyundai Kona Limited	39
Renault Zoe	52	Volvo Xc40	75

3.1.1.2 Objective function

The objective function of the defined optimization problem is determined as the minimization the TEC as shown in (2.2) (Beyazıt et al., 2022).

$$TEC = \sum_{h\in H, e\in E, t\in T}(\lambda_t^{buy} \times (P_{h,t}^{buy,G} + P_{h,t}^{buy,L} + P_{e,t}^{G\rightarrow EV}) - \lambda_t^{sell} \times (P_{h,t}^{sell,G} + P_{h,t}^{sell,L} + P_{e,t}^{EV\rightarrow G}) + (C_e^{deg} \times P_{e,t}^{EV,dch})) \times \Delta T \quad (2.2)$$

3.1.1.3 Power constraints

As shown in (2.3), the amount of power provided to each house at a certain time is divided into four components: $P_{h,t}^{buy,L}$ defines the power provided from surplus PV power of other houses to house h while $P_{h,t}^{buy,G}$ denotes the power purchased from the grid, then $P_{h,t}^{buy,ESS}$ and $P_{e,t}^{buy,EV}$ are the power supplied from shared ESS and EV e respectively. Similarly, the amount of power provided by each house at a given moment consists of four components as in (2.4): $P_{h,t}^{sell,L}$ defines the power provided from house h to other houses while $P_{h,t}^{sell,G}$ denotes the power sold from house h to the grid, then $P_{h,t}^{sell,ESS}$ and $P_{e,t}^{sell,EV}$ are the power transferred from house h to the shared ESS and EV e respectively. In addition, (2.5) expresses that the total received and transferred local power within the neighborhood should be equal to each other in time period t in order to maintain a balance of the purchased and sold energy between the houses in the neighborhood. (2.6) states the power consumed by the neighborhood through the transformer whereas (2.7) designates the power sold by the houses in the neighborhood via transformer. Constraint (2.8) represents the power flow from the grid to the neighborhood, ESS and EVs through the transformer. In constraint (2.9), on the other hand, the power flowed to the grid through the transformer is shown. The total power flow through the transformer is limited by (2.10) and (2.11). Besides, the bidirectional power flow is prevented by the binary variable in (2.10) and (2.11) since the bidirectional power flow is unavailable in the same time period for transformers.

$$P_{h,e,t}^{buy,T} = P_{h,t}^{buy,G} + P_{h,t}^{buy,L} + P_{h,t}^{buy,ESS} + P_{e,t}^{buy,EV}, \forall\, h, e, t \tag{2.3}$$

$$P_{h,e,t}^{buy,T} = P_{h,t}^{buy,G} + P_{h,t}^{buy,L} + P_{h,t}^{buy,ESS} + P_{e,t}^{buy,EV}, \forall\, h, e, t \tag{2.4}$$

$$\sum\nolimits_{h \in H} P_{h,t}^{buy,L} = \sum\nolimits_{h \in H} P_{h,t}^{sell,L}, \forall\, t \tag{2.5}$$

$$\sum\nolimits_{h \in H} P_{h,t}^{buy,G} = P_t^{G \to N}, \forall\, t \tag{2.6}$$

$$\sum\nolimits_{h \in H} P_{h,t}^{sell,G} = P_t^{N \to G}, \forall\, t \tag{2.7}$$

$$P_t^{G \to TR} = P_t^{G \to N} + P_t^{G \to ESS} + \sum\nolimits_{e \in E} P_{e,t}^{G \to EV}, \forall\, t \tag{2.8}$$

$$P_t^{TR \to G} = P_t^{N \to G} + P_t^{ESS \to G} + \sum\nolimits_{e \in E} P_{e,t}^{EV \to G}, \forall\, t \tag{2.9}$$

$$P_t^{G \to TR} \le P^{TR} \times b_t^1, \forall\, t \tag{2.10}$$

$$P_t^{TR \to G} \le P^{TR} \times (1 - b_t^1), \forall\, t \tag{2.11}$$

The formulation of shared ESS model is depicted by (2.12)-(2.20). Constraints (2.12) and (2.13) limits the charge and discharge capacities of the shared ESS. Furthermore, the binary variable in (2.12) and (2.13) prevents the shared ESS from being charged and discharged at the same time period. Equation (2.14) expresses the SoE of the shared ESS while the SoE at each time period is limited by the minimum and maximum SoE values in (2.15). The initial SoE of the shared ESS is determined by (2.16). The battery is charged by the power drawn from the neighborhood and drawn from the grid through neighborhood transformer as represented in (2.17). Similarly, (2.18) shows that the shared ESS is discharged by the power transferred from the shared ESS to the houses in the neighborhood and to the power grid. Finally, (2.19) and (2.20) represent the total purchased power from ESS and the total sold power to the ESS by the neighborhood, respectively.

$$0 \leq P_t^{ESS,ch} \leq P_{ESS}^{CH} \times b_t^2, \forall\, t \tag{2.12}$$

$$0 \leq P_t^{ESS,dch} \leq P_{ESS}^{DCH} \times (1 - b_t^2), \forall\, t \tag{2.13}$$

$$SOE_t^{ESS} = SOE_{t-1}^{ESS} + \eta^{CH} \times P_t^{ESS,ch} \times \Delta T - P_t^{ESS,dch} / \eta^{DCH} \times \Delta T, \quad if\ t > 1 \tag{2.14}$$

$$SOE^{ESS,min} \leq SOE_t^{ESS} \leq SOE^{ESS,max}, \forall\, t \tag{2.15}$$

$$SOE_t^{ESS} = SOE^{ESS,0}, \quad if \quad t = 1 \tag{2.16}$$

$$P_t^{ESS,ch} = P_t^{N \to ESS} + P_t^{G \to ESS}, \forall\, t \tag{2.17}$$

$$P_t^{ESS,dch} = P_t^{ESS \to N} + P_t^{ESS \to G}, \forall\, t \tag{2.18}$$

$$P_t^{ESS \to N} = \sum_{h \in H} P_{h,t}^{buy,ESS}, \forall\, t \tag{2.19}$$

$$P_t^{N \to ESS} = \sum_{h \in H} P_{h,t}^{sell,ESS}, \forall\, t \tag{2.20}$$

The formulation of EV charge-discharge model is described by the constraints (2.21)-(2.27). The constraints (2.21) and (2.22) limit the charging and discharging powers of EVs, respectively. However, the binary variables at (2.21) and (2.22) allow only one-direction power flow from or to each EV. Equation (2.23) represents the SoE of the EVs while SoE of each EV is limited at maximum 100% and minimum 20% by (2.24) to prevent the overcharge and deep of discharge.

Constraint (2.25) states that at the arrival time, SoE of each EV is equal to its initial value. The power balance between EVs and the transformer or neighborhood for charging and discharging EVs is shown in constraints (2.26) and (2.27).

$$0 \leq P_{e,t}^{EV,ch} \leq P_{EV}^{CH} \times b_{e,t}^{3}, \forall\, t \tag{2.21}$$

$$0 \leq P_{e,t}^{EV,dch} \leq P_{EV}^{DCH} \times \left(1 - b_{e,t}^{3}\right), \forall\, t \tag{2.22}$$

$$SOE_{e,t}^{EV} = SOE_{e,t-1}^{EV} + \eta^{CH} \times P_{e,t}^{EV,ch} \times \Delta T - P_{e,t}^{EV,dch} / \eta^{DCH} \times \Delta T, \quad if\ t > 1 \tag{2.23}$$

$$SOE_{e}^{EV,min} \leq SOE_{e,t}^{EV} \leq SOE_{e}^{EV,cap}, \forall\, e, t \tag{2.24}$$

$$SOE_{e,t}^{EV} = SOE_{e}^{EV,0}, \forall\, e;\ if\ t = T_{arr} \tag{2.25}$$

$$P_{e,t}^{EV,ch} = P_{e,t}^{N \to EV} + P_{e,t}^{G \to EV}, \forall\, e, t \tag{2.26}$$

$$P_{e,t}^{EV,dch} = P_{e,t}^{EV \to N} + P_{e,t}^{EV \to G}, \forall\, e, t \tag{2.27}$$

The power constraints of each house are shown by (2.28)-(2.31). Constraint (2.28) provides the balance between load demand and power supplied from grid and PV system. With the binary variables in constraints (2.29) and (2.30), the houses can either deliver power to or draw power from the grid at each time period since the unavailability of a bidirectional power flow in the same time period. Equation (2.31) states that the PV power generation can be utilized by the houses and surplus power, if any, is delivered to the power grid in order to gain profit.

$$P_{h,e,t}^{buy,T} + P_{h,t}^{PV,used} = LD_{h,t}, \forall\, h, e, t \tag{2.28}$$

$$P_{h,e,t}^{buy,T} \leq K \times b_{h,e,t}^{4}, \forall\, h, e, t \tag{2.29}$$

$$P_{h,e,t}^{sell,T} \leq K \times \left(1 - b_{h,e,t}^{4}\right), \forall\, h, e, t \tag{2.30}$$

$$P_{h,t}^{PV,used} + P_{h,e,t}^{sell,T} = P_{h,t}^{PV}, \forall\, h, e, t \tag{2.31}$$

3.1.1.4 Energy management strategy

The primary target of the proposed strategy is to schedule the use of both the shared ESS and EV batteries and to exploit their potential in terms of providing distribution system flexibility and reducing the energy costs of end-users (Beyazıt et al., 2022). When the PV-integrated residential end-users are considered, the PV power production rarely coincides with the peak demand of the houses. Besides, assuming a dynamic price tariff is imposed in a residential area, the peak price of electricity usually occurs naturally during peak hours. Consequently, as the PV production does not coincide with peak price period, it is obvious that the excess PV energy is usually sold back to power grid at lower prices and energy demand is met by power grid with higher prices.

To overcome the aforementioned problem by integrating an ESS unit into the system, the excess PV power produced during the day is stored in the ESS unit and used during peak hours. Thus, the end-users exploit the PV system better and reduce their energy costs.

In the proposed system, each household in the neighborhood gains energy credits as much as the total energy it sent to the neighborhood, to shared ESS and to the grid until it reaches the credit limit designated by the LSE through the ECM. With this ECM implemented, the end-users can use the credits during peak hours to satisfy the energy demand through the DR program, which is provided by the LSE and assumed to be participated by each household.

On the other hand, it is considered that the households have EVs of different models and battery capacities in this study. In the proposed strategy, a part of the residual energy demand is met by the EV batteries rather than purchasing energy from the power grid. The V2G and V2H services, which are profitable for both the EV user and the LSE, aim to reduce the peak load by delivering the energy in the EV batteries to the power grid or the houses. These services are suitable for use in PLR-based DR applications as the arrival time of EVs to the EVCS and the peak hours generally coincide. The LSE manages the EV fleet so that it discharges during peak hours using the DR program and V2G/V2H capability, and charges during off-peak hours.

The formulation of the energy management strategy is expressed by (2.32)-(2.45). Energy credit of each house varies by transferring energy to the shared ESS or drawing energy from it, as shown in constraint (2.32). The initial energy credit of each house at first time step is determined by (2.33). The energy credit obtained by each house is limited by (2.34) depending on the PV system capacity and SoE of shared ESS as defined in constraint (2.35). In order for each household to be able to use all of their energy credits during the DR event, the shared ESS's battery capacity should be greater than or equal to the total energy credit plus the shared ESS's minimum SoE level at the beginning of the DR event, as expressed in (2.36). On the other hand, the energy credit of each EV varies depending on the transferred energy from or to EV batteries as shown in constraint (2.37) while constraint (2.38) defines the initial energy credit value of each EV at the start of the DR event.

Moreover, constraints (2.39)-(2.45) are designed to exploit the shared ESS and EV batteries. Constraints (2.39) and (2.40) prevent the energy transfer to the shared ESS during DR period and from the shared ESS to the neighborhood during outside the DR period, respectively. Constraints (2.41) and (2.42) prevent the charging of the EVs during the DR period while constraints (2.43) and (2.44) prevent the discharging of the EVs outside the DR period. Finally, constraint (2.45) requires that each EV batteries charge to 100% SoE until the next day.

$$E_{h,t}^{Crd} = E_{h,t-1}^{Crd} + \left(P_{h,t}^{sell,ESS}\right) \times \Delta T - \left(P_{h,t}^{buy,ESS}\right) \times \Delta T, \forall\, h,t;\ \ if\ \ t > 1 \quad (2.32)$$

$$E_{h,t}^{Crd} = E_{h}^{Crd,0}, \forall\, h;\ \ if\ \ t = 1 \quad (2.33)$$

$$E_{h,t}^{Crd} \leq E_{h}^{Crd,max}, \forall\, h,t \quad (2.34)$$

$$E_{h}^{Crd,max} = \left(SOE^{ESS,max} - SOE^{ESS,0}\right) \times PV_{h}^{cap} / PV^{cap,tot}, \forall\, h \quad (2.35)$$

$$SOE_{t}^{ESS} \geq \sum_{h \in H} E_{h,t}^{Crd} + SOE^{ESS,min},\ \ if\ \ t = T^{DR.start} \quad (2.36)$$

$$E_{e,t}^{Crd,EV} = E_{e,t-1}^{Crd,EV} + \left(P_{e,t}^{sell,EV}\right) \times \Delta T - \left(P_{e,t}^{buy,EV}\right) \times \Delta T, \forall\, e,t; \quad (2.37)$$
$$if\ \ t \geq T^{DR,start}$$

$$E_{e,t}^{Crd,EV} = E_{e}^{Crd,EV0}, \forall\, h;\ \ if\ \ t = T^{DR,start} \quad (2.38)$$

$$P_{h,t}^{sell,ESS} = 0, \forall\, h,t\ \in \left[T^{DR,start}, T^{DR,end}\right] \quad (2.39)$$

$$P_{h,t}^{buy,ESS} = 0, \forall\, h, t \notin [T^{DR,start}, T^{DR,end}] \tag{2.40}$$

$$P_{e,t}^{sell,EV} = 0, \forall\, e, t \in [T^{DR,start}, T^{DR,end}] \tag{2.41}$$

$$P_{e,t}^{G\rightarrow EV} = 0, \forall\, e, t \in [T^{DR,start}, T^{DR,end}] \tag{2.42}$$

$$P_{e,t}^{buy,EV} = 0, \forall\, e, t \notin [T^{DR,start}, T^{DR,end}] \tag{2.43}$$

$$P_{e,t}^{EV\rightarrow G} = 0, \forall\, e, t \notin [T^{DR,start}, T^{DR,end}] \tag{2.44}$$

$$SOE_{e,t}^{EV} = SOE_{e}^{EV,cap} \; if \;\; t = T^{end} \tag{2.45}$$

3.2 Optimal Management of Mobile Charging Stations in Urban Areas in A Distribution Network

3.2.1 System description and mathematical model

In this study, an energy management strategy consisting of MCSs, a depot for charging MCSs and EV charging demands in different locations is presented as shown in Figure 3.2 (Beyazit and Tascikaraoglu, 2022). The map shows charging locations determined by EV users. MCSs satisfy the demands by determining the most appropriate route based on EV charging characteristics (charging time, desired SoE, charging location, etc.).

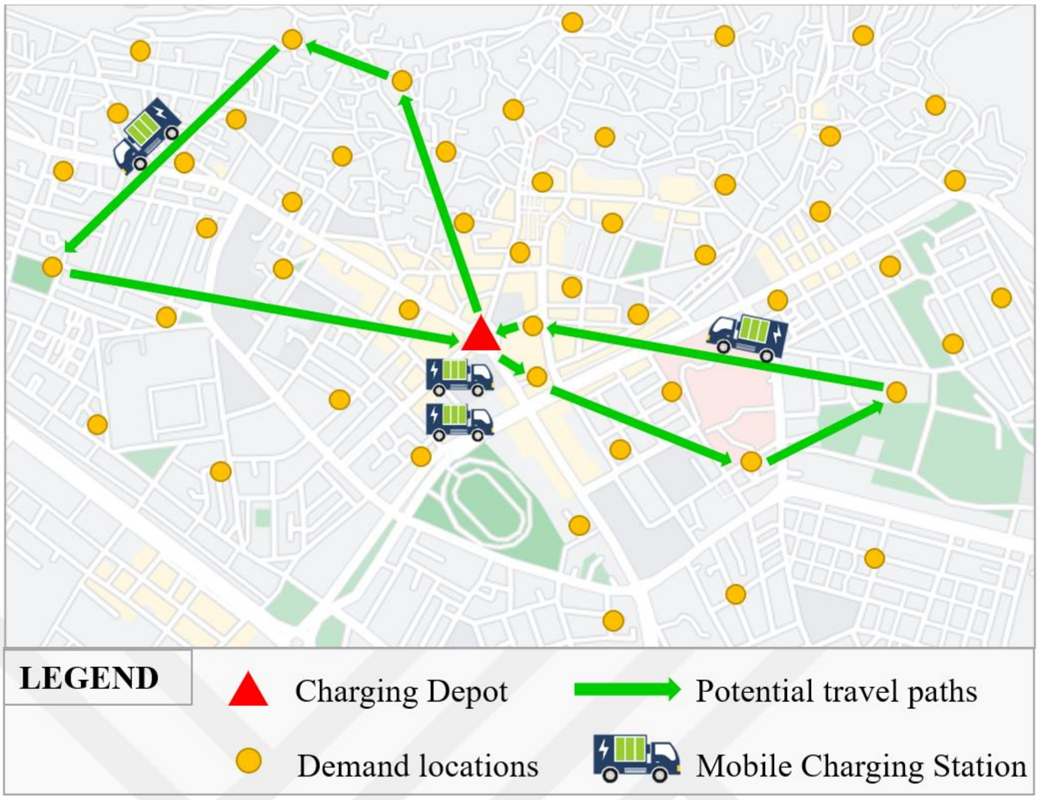

Figure 3.2. The mapping scheme of the proposed system.

3.2.1.1 Objective function

The objective function of the defined optimization problem is determined as minimizing the total operation costs of the MCSs as shown in (3.1) (Beyazit and Tascikaraoglu, 2022).

$$min \sum_{m,i,t} \lambda_t^{buy} \times P_{m,i,t}^{ch,MCS} \times \Delta T - \sum_{m,i,t} \lambda_t^{sell} \times P_{m,i,t}^{dis,MCS} \times \Delta T \quad (3.1)$$

3.2.1.2 Power constraints

The total charge and discharge power of each MCS in the time interval t is given by (3.2) and (3.3). Equation (3.4) states MCSs charging power is limited by P_{MCS}^{CH} power in the $0 \leq t \leq \gamma^{ch}$ time interval. With constraint (3.5), the MCSs are only allowed to charge at the depot due to the lack of charging station near the demand locations. The constraints (3.6) and (3.7) ensure that the charging demand at each node i is fully met by the MCSs within the determined time window. Constraint (3.8) specifies the allowed maximum discharge power for MCSs. In addition, binary variable $x_{m,i,j}$ in

(3.8) provides that the MCS can only discharge when the (i,j) path is available. Constraints (3.9) and (3.10) indicate that MCSs cannot be discharged at the depot and demands cannot be met outside the time interval determined by the user, respectively.

$$P_{m,t}^{ch,MCStot} = \sum_{i \in V_0} P_{m,i,t}^{ch,MCS}, \forall\, m \in M, t \in T \tag{3.2}$$

$$P_{m,t}^{dis,MCStot} = \sum_{i \in V'} P_{m,i,t}^{dis,MCS}, \forall\, m \in M, t \in T \tag{3.3}$$

$$P_{m,t \in T}^{ch,MCStot} \leq P_{MCS}^{CH}, \forall\, m \in M, t \leq \gamma^{ch} \tag{3.4}$$

$$P_{m,i,t \in T}^{ch,MCS} = 0, \forall\, m \in M, i \in V' \tag{3.5}$$

$$P_{i}^{dis,MCS} = \sum_{m \in M, t \in T} P_{m,i,t}^{dis,MCS}, \forall\, i \in V' \tag{3.6}$$

$$P_{i}^{dis,MCS} = ED_i^{EV}, \forall i \in V' \tag{3.7}$$

$$P_{m,j,t \in T}^{dis,MCS} \leq P_{MCS}^{DCH} \times x_{m,i,j}, \forall m \in M, i,j \in V', (i,j) \in A \tag{3.8}$$

$$P_{m,i,t \in T}^{dis,MCS} = 0, \forall\, m \in M, i \in V_0 \tag{3.9}$$

$$P_{m,i,t \in T}^{dis,MCS} = 0,\ \forall\, m \in M, i \in V', t < t_i^{low}\ or\ t > t_i^{up} \tag{3.10}$$

3.2.1.3 State-of-energy constraints

Equation (3.11) depicts the SoE of the MCSs whereas (3.12) limits the SoE of each MCS at maximum 100% and minimum 0% to avoid overcharge and deep of discharge. Besides, as shown in (3.11) the required energy for travelling is satisfied from internal battery of MCSs. If path is available, it is determined in (3.13) whether the SoE of MCS m in node i is sufficient to complete the travel between (i,j) and satisfy the charging demand at the next node j. The energy required for MCSs travel is defined by (3.14) based on distance between demand locations.

$$SOE_{m,t}^{MCS} = SOE_{m,t-1}^{MCS} + (P_{m,t}^{ch,MCStot} \times \Delta T \times \eta^{ch}) - (P_{m,t}^{dis,MCStot} / \Delta T \times \eta^{dis}) - E_{m,t}^{tr}, \forall\, i \in V, t \in T \quad (3.11)$$

$$0 \leq SOE_{m,t}^{MCS} \leq SOE^{MCS,cap}, \forall\, m \in M, t \in T \quad (3.12)$$

$$SOE_{m \in M, t \in T}^{MCS} \geq (ED_j^{EV} + E_{m,i,j}^{tr}) \times x_{m,i,j}, \forall i, j \in V, \forall\, (i,j) \in A, i \neq j \quad (3.13)$$

$$E_{m,t}^{tr} = E^{tr,unit} \times D_{i,j} \times x_{m,i,j}, \forall\, m \in M, \forall\, (i,j) \in A, t \in T \quad (3.14)$$

3.2.1.4 Spatial temporal constraints

Spatial constraints are given between (3.15)-(3.18). Constraint (3.15) and (3.16) ensure that exactly N MCS depart from and arrive at depot, respectively. Besides, (3.17) and (3.18) ensure that each node should be visited just once. As a result, MCSs leave the depot once during the operation period to visit demand locations and then return after finishing the charging service.

Temporal constraints are given between (3.19)-(3.24). τ is a decision variable specifying the time of starting services for EV demands. (3.19) and (3.20) indicate that to start charging service at node j, the decision variable $\tau_{m,j}^{start,dis}$ must be greater than the charge/discharge time at node i plus the time spent on the road for the MCS m. Thus, it is verified whether the requested charging start time is satisfied before travelling from node i to j. Also, in the absence of (i,j) path for MCS m, a sufficiently large number K is used to prevent discharging at node j.

In (3.21) and (3.22) it is ensured that the charging time is less than γ^{ch}. Likewise, in (3.23) and (3.24), the discharge time is provided to be inside the time window determined by the users. Thus, charging services cannot start before the t_i^{low} and end after t_i^{up}, and the early arrival of MCSs may result waiting time.

$$\sum_{j \in V} x_{i,j} = N, \forall\, i \in V_0, (i,j) \in A, i \neq j \quad (3.15)$$

$$\sum_{j \in V} x_{j,i} = N, \forall\, i \in V_0, (i,j) \in A, i \neq j \quad (3.16)$$

$$\sum_{i \in V} x_{i,j} = 1, \forall\, j \in V, (i,j) \in A, i \neq j \quad (3.17)$$

$$\sum_{j \in V} x_{i,j} = 1, \forall\, i \in V, (i,j) \in A, i \neq j \tag{3.18}$$

$$\tau_{m,i}^{start,ch} + \left(t_{i,j} + T_{m,i}^{ch,tot}\right) \times x_{m,i,j} + K \times \left(1 - x_{m,i,j}\right) \leq \tau_{m,j}^{start,dis}, \tag{3.19}$$
$$\forall\, m \in M, i \in V_0, j \in V', (i,j) \in A, i \neq j$$

$$\tau_{m,i}^{start,dis} + \left(t_{i,j} + T_{m,i}^{dis,tot}\right) \times x_{m,i,j} + K \times \left(1 - x_{m,i,j}\right) \leq \tau_{m,j}^{start,dis}, \tag{3.20}$$
$$\forall\, m \in M, i,j \in V', (i,j) \in A, i \neq j$$

$$0 \leq \tau_{m,i}^{start,ch} \leq \gamma^{ch}, \forall\, m \in M, i \in V_0 \tag{3.21}$$

$$0 \leq \tau_{m,i}^{end,ch} \leq \gamma^{ch}, \forall\, m \in M, i \in V_0 \tag{3.22}$$

$$t_i^{low} \leq \tau_{m,i}^{start,dis} \leq t_i^{up}, \forall\, m \in M, i \in V' \tag{3.23}$$

$$t_i^{low} \leq \tau_{m,i}^{end,dis} \leq t_i^{up}, \forall\, m \in M, i \in V' \tag{3.24}$$

4. ASSESSMENT OF THE FINDINGS

4.1 Cost Optimization of A Microgrid Considering Vehicle-to-Grid Technology and Demand Response

4.1.1 Input data

PV power production and load demand measurements belonging to a set of houses in a region Austin, TX, USA were obtained from (Taşcıkaraoğlu, 2018). High PV power production potential of the location and the availability of the high-resolution data (i.e., recorded for each five minute) are the key factors in selecting this dataset. The data of 40 detached houses are selected from this region and assumed that the houses compose a neighborhood with their own solar panels and EVs. The energy consumption and PV production of the neighborhood are demonstrated together in Figure 4.1. When considering the variation of PV production and load demand of the houses, it remarks that the supply and demand data do not usually overlap with each other, which implies that the neighborhood can be a good environment to implement a shared ESS. Since battery sizing and cost are beyond the scope of this study, it is assumed that a shared ESS of 300 kWh is deployed in the microgrid, considering the worst case when there is an overloading on the power grid with very limited sunlight. Nevertheless, the battery capacity is increased or decreased by ±50% in the case studies to demonstrate the effects of the shared ESS with different capacities on the results. Besides, it should be stated that a real-time pricing tariff adopted from (Taşcıkaraoğlu, 2018) is utilized for the electricity price, as shown in Figure 4.2.

Also, the most popular ten EV models in the market that have 11 kW charging rate through Type-2 EVCS are considered in the study in order to achieve more realistic assessments, as demonstrated in Table 3.1 (Grove, 2021). It is assumed that the Type-2 EVCS provides the maximum charging/discharging power of 22 kW and a charging/discharging efficiency of 0.98 (Chen et al., 2021). Finally, the key parameters for the constituents employed in the proposed system are listed in Tables Table 4.1 and Table 4.2. The EV departure/arrival behavior and the initial SoE of EVs (at the arrival time of EVs at the EVCS) are some uncertainties in the EV charging/discharging model. In order to obtain stochastic EV departure/arrival times, two-parameter Weibull distribution is applied by adapting the original data from (Sengor et al., 2021). Two-parameter Weibull distribution function is expressed by (2.46) in which x is the time bin, α and β are the shape and the scale parameters, respectively.

$$F(x) = 1 - e^{-(\frac{x}{\beta})^{\alpha}} \tag{2.46}$$

Table 4.1. Key parameters of the proposed system

Constituents	Parameters	Initial Value	Minimum Value	Maximum Value	Units
Neighborhood Transformer	P^{TR}	-	-	2000	kW
PV System	PV_h^{cap}	-	5	11	kW
	$PV^{cap,tot}$	-	-	285	kW
EV Fleet	P_{EV}^{CH}/P_{EV}^{DCH}	-	-	11	kW
	C_e^{deg}	-	0.0221	0.0235	$/kWh
	SOE_e^{EV}	9.7-53.1[a]	5.8-16	28.9-80	kWh
	E_e^{Crd}	1.8-37.1[a]	0	1.8-37.1	kWh

[a]At starting of DR event (7:00 p.m.).

Table 4.2. Key parameters of the shared ESS for various case studies

Parameters	Initial Value			Minimum Value			Maximum Value			Units
	Case 2&4	Case 1,3&5	Case 6	Case 2&4	Case 1,3&5	Case 6	Case 2&4	Case 1,3&5	Case 6	
$P_{ESS}^{CH}/P_{ESS}^{DCH}$	-	-	-	-	-	-	30	60	90	kW
SOE^{ESS}	75[a]	150[a]	225[a]	30	60	90	150	300	450	kWh
E_h^{Crd}	0[a]	0[a]	0[a]	0	0	0	2.1-4.6	4.2-9.3	6.3-13.9	kWh

[a]At starting of day (7:00 a.m.).

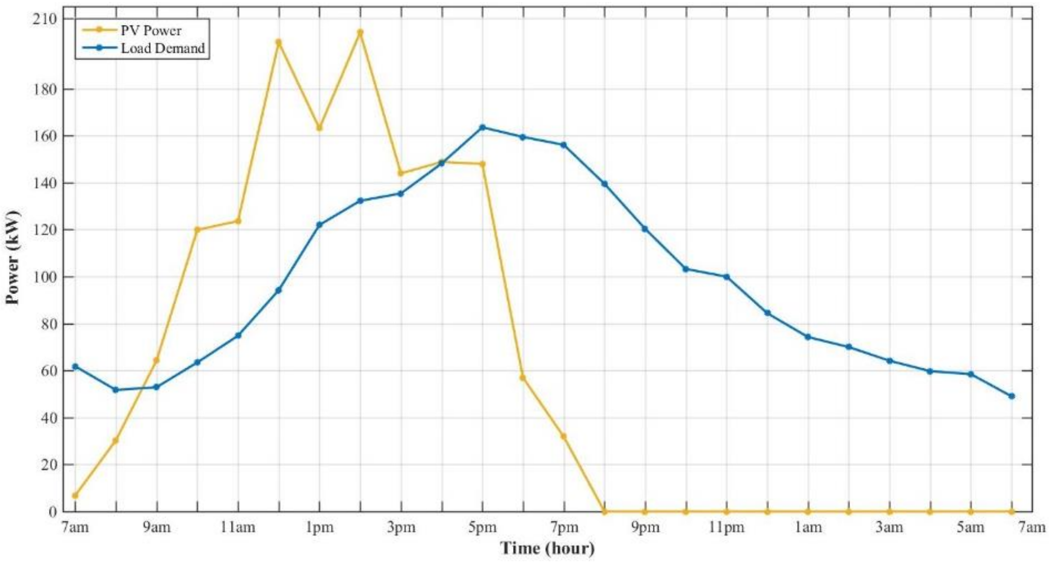

Figure 4.1. PV power output and load demand in a test period of one day.

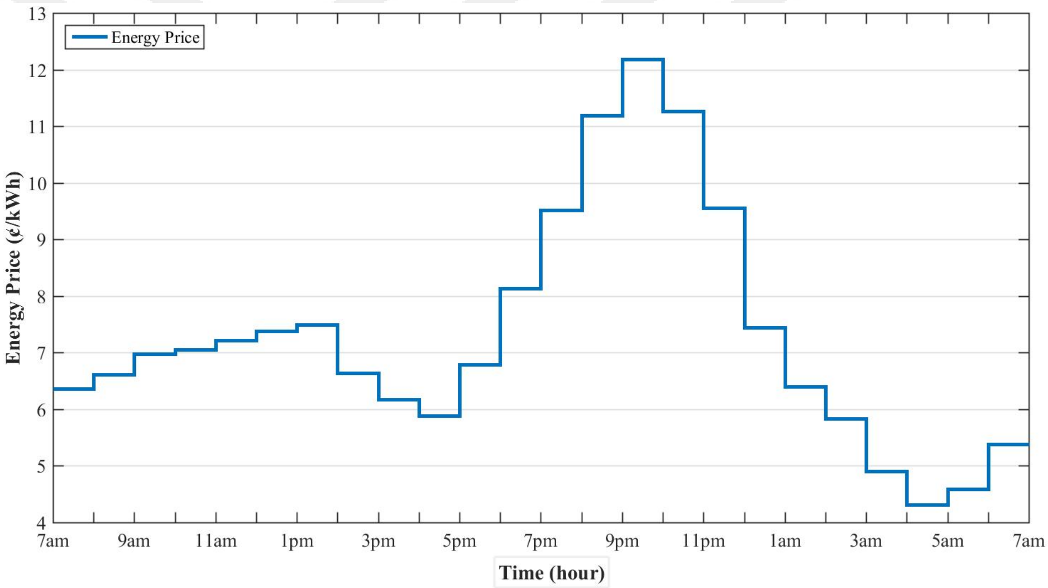

Figure 4.2. Price variation in a test period of one day.

Appropriate α and β values are found by using MATLAB *dfittool* as 1.59 and 4.08 for departure, and 1.47 and 4.04 for arrival, respectively. Figure 4.3 shows the departure/arrival times distribution with 15-minute time intervals for departure from 7:00 a.m. to 9:30 a.m. and for arrival from 4:30 p.m. to 7:00 p.m. It should be stated that a weekday when EV users leave their houses in the early morning and arrive at EVCS at the end of the working hours is considered in the proposed strategy. Accordingly, the starting and ending times of one day test period are determined as 7:00 a.m. and 6:59 a.m., respectively. In addition, the DR event period is determined between 7:00 p.m. and 11:00 p.m., considering the EVs' arrival times and peak load demand hours. On the other hand, the initial SoE level of each EV is obtained randomly using normal distribution as represented in Figure 4.4. Mean and standard deviation values are defined as μ = 50% and σ = 9.55%, respectively. It should be stated that the proposed optimization method is tested using General Algebraic Modeling System (GAMS) v.25.1.3 software and solver CPLEX. It takes 0.56 s to solve the mixed integer problem using a Quad Core Laptop with 2.5 GHz CPU and 8 GB RAM.

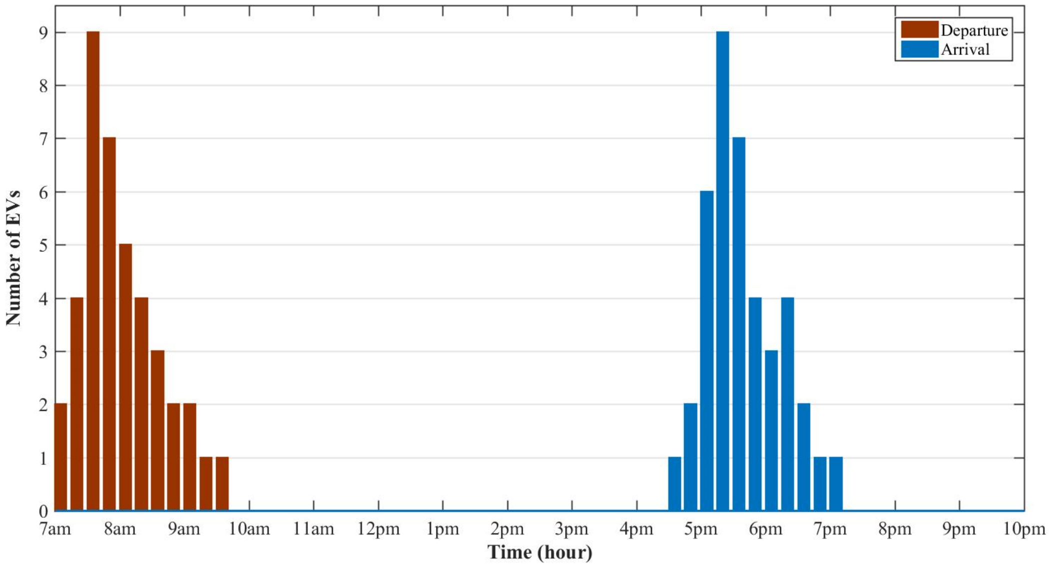

Figure 4.3. The departure/arrival times distribution.

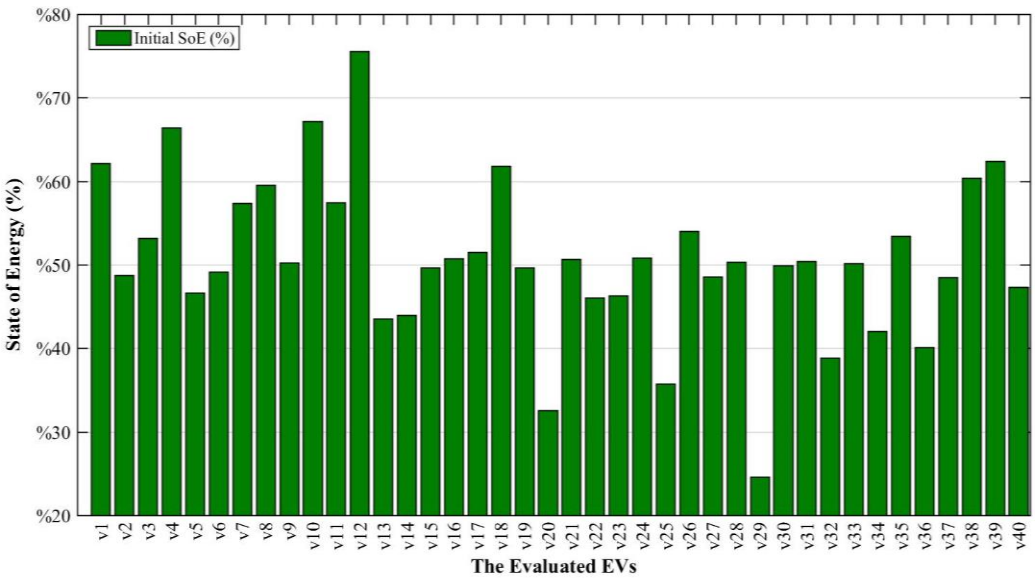

Figure 4.4. The initial SoE variation of EVs before V2G/V2H operation.

4.1.2 Simulation and results

The effectiveness of proposed model is tested by considering a base case together with six different cases, as listed in Table 4.3:

Table 4.3. Case studies

Cases	DR	Shared ESS	ESS-to-Grid	V2G	V2H	ECM	
						Shared ESS	EV Fleet
Base Case	-	-	-	-	-	-	-
Case 1	✓	✓ (300kWh)	✓	-	-	✓	-
Case 2	✓	✓ (-50%)	-	-	✓	✓	✓
Case 3	✓	✓ (300kWh)	-	-	✓	✓	✓
Case 4	✓	✓ (-50%)	✓	✓	✓	✓	✓
Case 5[a]	✓	✓ (300kWh)	✓	✓	✓	✓	✓
Case 6	✓	✓ (+50%)	✓	✓	✓	✓	✓

[a]Proposed Case

First, in order to evaluate the potential benefits of the proposed method, V2G and V2H are not included in the first two cases and therefore only the charging schedule of EVs is considered in these cases. Since there is no energy management strategy, the Base Case can be considered as the worst case. In this case, the houses use their own PV energy first, then purchase the grid power if their production is less than their demand. Houses must satisfy their demand from grid during the peak price hours as the PV production is unavailable in the evening and nighttime. Figure 4.5 shows the variation of grid power and PV power consumed in the neighborhood for Case 1. In the first case, the houses first utilize their own PV generation and use the shared surplus PV power, named local power, instead of purchasing from the grid. Excess energy, if any, is stored in the shared ESS and used by the houses via ECM during DR period.

For Cases 2–6, EVs are not considered as a load required to be charged, instead they are also used as an energy storage option. Residual energy of the EV batteries is used for providing the household’s energy demand during the DR period in Case 2 and Case 3. Similar to the Case 1, the houses first utilize their own PV generation and local power in the daytime. Also, during DR period the houses have a chance to exploit both shared ESS and EV fleet’s batteries. On the other hand, EV users can sell their excess battery energy to the grid via the V2G service during the DR period in Cases 4, 5 and 6.

Cases 3, 4, and 6 are designed to investigate the effectiveness of the shared ESS on PLR and TEC with different battery capacities. Therefore, these cases are ignored in Figure 4.6 for the sake of simplicity since their graphical results are similar to those in the cases where the shared ESS with the original capacity (300 kWh) is used. For Cases 1, 2 and 5, the local power exchanges are shown in Figure 4.6. As seen in Figure 4.6, the local power variations overlap from 2:00 p.m. to 6:00 p.m. contrary to Case 2. The stored energy cannot be sold back to the grid due to the lack of bidirectional power flow for shared ESS and EV fleet in Case 2. Therefore, while the PV power transferred to the shared ESS decreases in Case 2, the local power exchange increases. The power drawn from the grid is given in Figure 4.7 for four different cases. Since Case 2 has a higher local power exchange, the grid power decreases between 4:00 p.m. and 6:00 p.m. Besides, as seen in Figure 4.7, the peak load demand of the purchased power from grid during the DR period is significantly reduced in Case 2 and Case 5. The use of higher grid power in Case 5 than in Case 2 is due to the fact that selling energy to the grid via V2G during the highest energy price period is more profitable than satisfying load demand in the neighborhood.

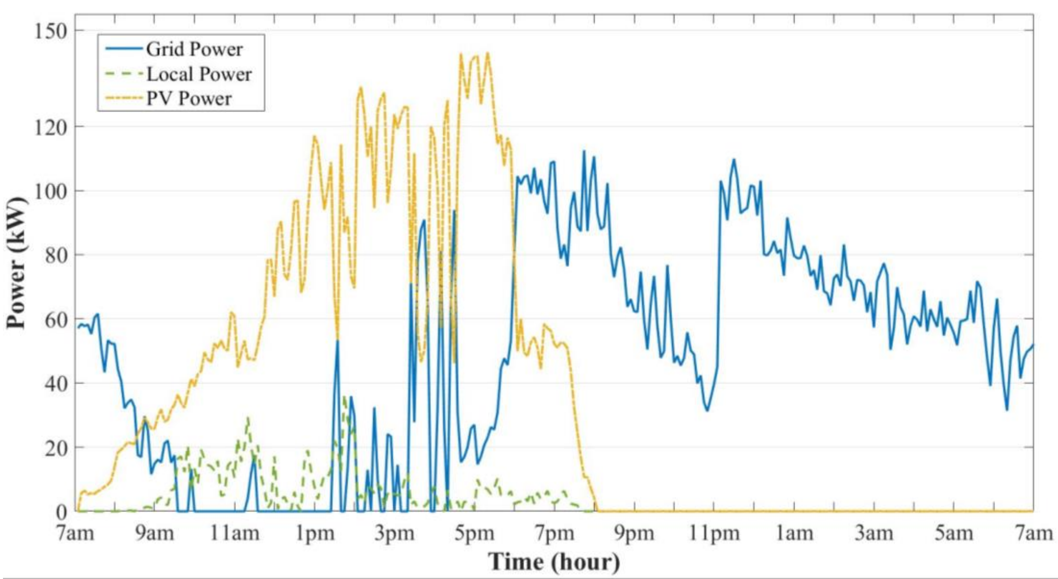

Figure 4.5. Power exchanges for Case 1 in a test period of one day.

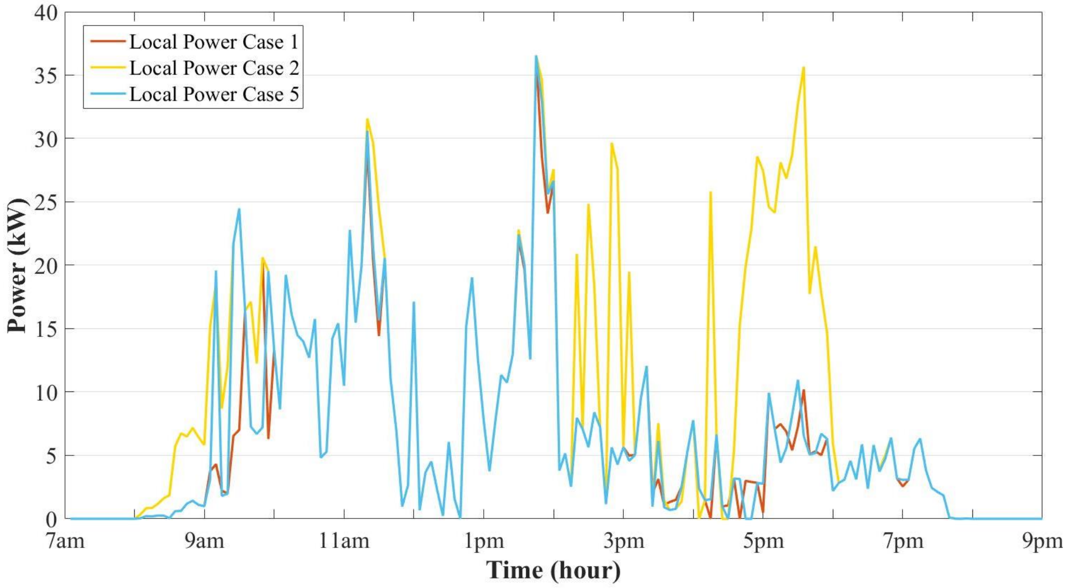

Figure 4.6. Local power exchange for three different cases in a test period of one day.

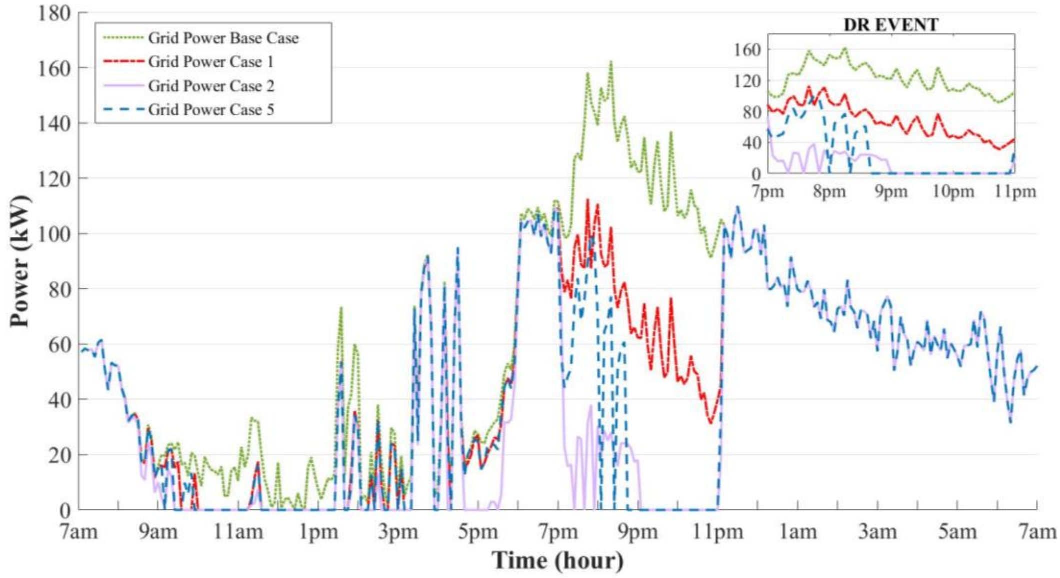

Figure 4.7. Grid power exchange for four different cases in a test period of one day.

The energy credits and SoE of the shared ESS are demonstrated for Cases 1–6 in Figure 4.8. The cases with different shared ESS capacities are split into two plots to demonstrate the variations of the SoE and energy credits explicitly. It is clear from Figure 4.8 that the SoE level of the shared ESS variations is similar for all the cases. This is because the shared ESS is used in all cases to minimize the TEC instead of drawing power from the grid. On the other hand, contrary to Cases 2 and 3, the power from the shared ESS sold to the grid between 10 a.m. and 2 p.m. is the reason of the ripples in the SoE. Besides, due to the small ESS capacity in Cases 2 and 4, the maximum energy credit limits are lower than the other cases as seen in Figure 4.8.

Figures Figure 4.9 and Figure 4.10 depict the change in the SoE level and energy credits of the EV fleet, respectively, based on the departure/arrival times and EV charge/discharge behaviors for Case 2 and Case 5. In these figures, the extremum values are indicated by the top and bottom horizontal black lines, respectively, whereas the median is shown by the middle red line in the box. In addition, the first and third quartiles are shown by the horizontal blue lines below and above the median. Since V2H and V2G services are employed together in Case 5, the batteries of the EV fleet are better exploited and energy credits are used in a more effective manner, as can be seen in these two figures. In order to compare Cases 1, 2 and 5 in terms of the SoE variation of the EVs, two random EVs, namely EV-1 and EV-40, are selected. The SoE variations starting from the arrival time of EVs to the next day are shown in Figure 4.11. Since the V2G/V2H services are unavailable in Case 1, only the charging operation is considered. Therefore, as can be seen in Figure 4.11, the SoE of the EVs remains at its initial level until the charging operation is started. The charging operation is carried out up to the full charge level during lowest electricity price periods.

In Case 2, the EVs transfer the power of their batteries to the houses with the different percentages of the SoE during on peak hours and then charge their batteries up to 100% as in the first case. On the other hand, in Case 5, the EVs deliver power to the grid and houses down to 20% during on-peak hours and then fully charge their batteries. It should be noted that due to the unavailability of V2G service for Case 2, some EVs with large battery packs, e.g., EV-40 in Figure 4.11, cannot be exploited down to 20%. As the SoE variation of the Base Case is similar to the first case, and Cases 3, 4 and 6 are similar to Cases 2 or 5, these cases are neglected in Figure 4.11 for a clearer representation.

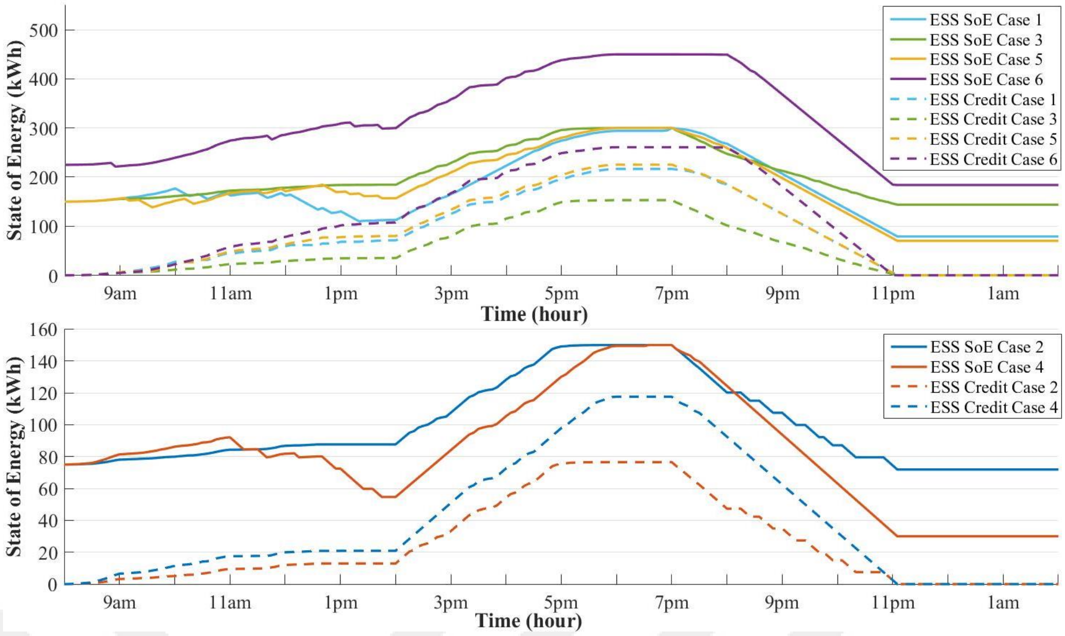

Figure 4.8. SoE and energy credit variation of shared ESS for all cases in a test period of one day.

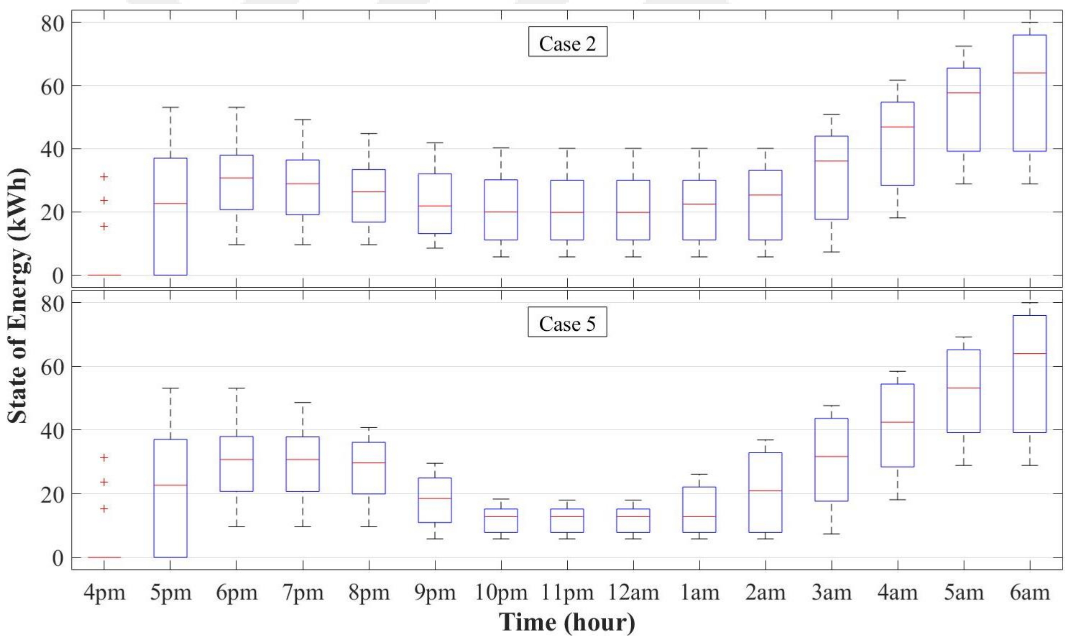

Figure 4.9. SoE level variation of EVs for Case 2 and 5 in a test period of one day.

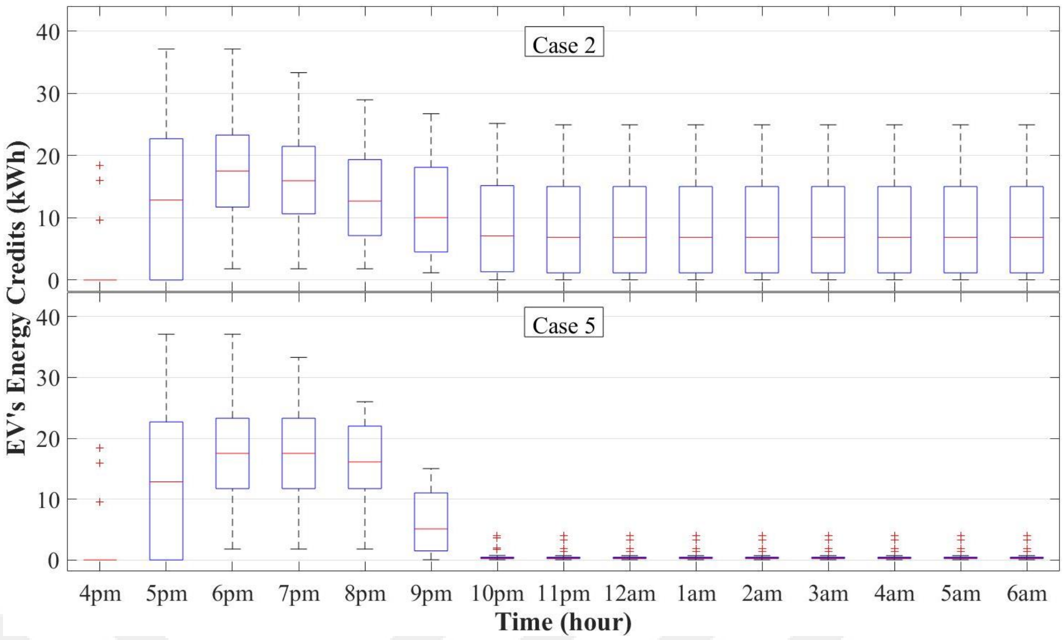

Figure 4.10. Energy credit variation of EVs for Case 2 and 5 in a test period of one day.

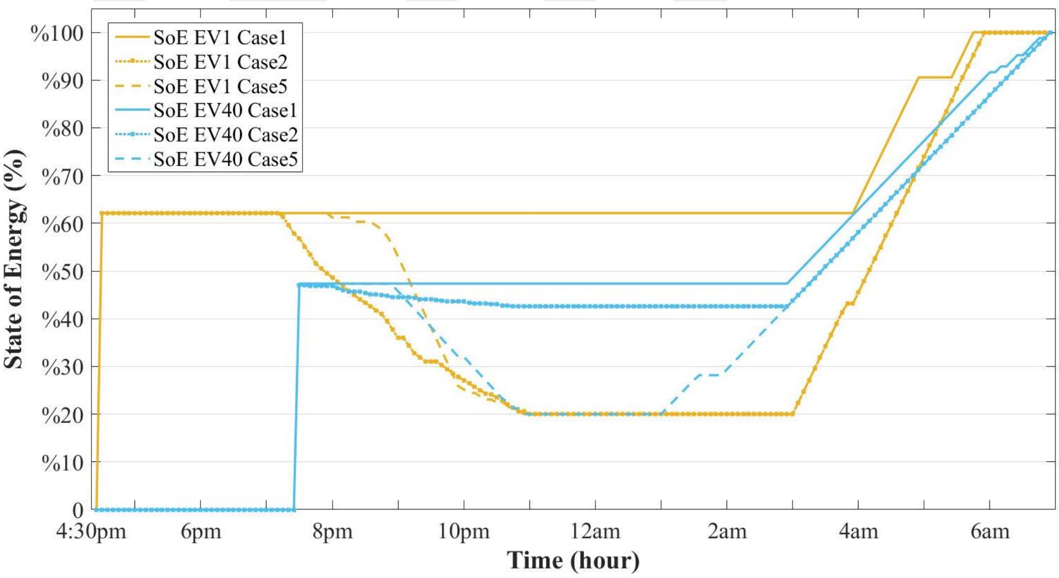

Figure 4.11. SoE level variation of selected EVs for Case 1, Case 2 and Case 5 in a test period of one day.

Another important result can be obtained by comparing the PLR values, which are calculated by (2.47) and equal to the total power provided by the ESS and EV fleet to the grid and the houses during DR event, as shown in Figure 4.12. Since Case 3 has 50% more shared ESS capacity than Case 2, the utilization of EV batteries is reduced, resulting in less battery degradation and lower energy costs. However, as the stored energy cannot be sold back to the grid in Case 3, increasing shared ESS capacity has only a small impact on the PLR and TEC. On the other hand, both Cases 2 and 3 have considerable PLR value compared to Case 1 since the ECM is available for both the shared ESS and EV fleet.

$$PLR = \sum_t P_t^{ESS,dch} + \sum_{t,e\in E} P_{e,t}^{EV,dch} \quad ,t \in [T^{DR,start}, T^{DR,end}] \qquad (2.47)$$

Besides, the V2G service that is available in Cases 4, 5 and 6 provides a significant PLR compared to other cases. Due to the discharging power constraints and limited DR period, increasing shared ESS capacity by 50% in Case 6 has a small effect on both PLR and TEC, as shown in Figure 4.12 and Table 4.4. Finally, from the view of the LSEs, the proposed approach considerably reduces the peak load demand, which is a crucial challenge during stressful conditions for the grid.

The comparison of the main results for the cases is given in Table 4.4. While the total purchased energy is 2648.11 kWh for the Base Case, it decreases to 2392.83 kWh, 2453.11 kWh and 2388.92 kWh for Cases 1, 2 and 3, respectively. After implementing the V2G service, the EV batteries are exploited until its minimum permissible SoE level, then recharged up to 100% SoE during off-peak hours. Thus, the purchased energy increases for Cases 4, 5 and 6 compared to Base Case while the TEC decreases. Contrary to the other cases, there is no energy sold to the grid in Base Case in which the DR event is unavailable. Only the excess PV energy can be sold directly to the grid in Cases 2 and 3, hence the sold energy is lower than those in the other cases. Although the V2G and ESS-to-grid are not available, Cases 2 and 3 provide the acceptable level of PLR and TEC compared to Base Case and Case 1. Besides, Case 3 has the lowest battery degradation cost (710.21 ¢), followed by Case 2 (836.30 ¢). These results validate the effectiveness of the proposed ECM in the lack of bidirectional power flow for the shared ESS and EV fleet. Also, the proposed method procures a significant cost saving for the houses in the neighborhood as seen in Table 4.4. As a result, Case 5, which includes the shared ESS of 300 kWh, V2G/V2H services and ECM, is found as the most optimal case.

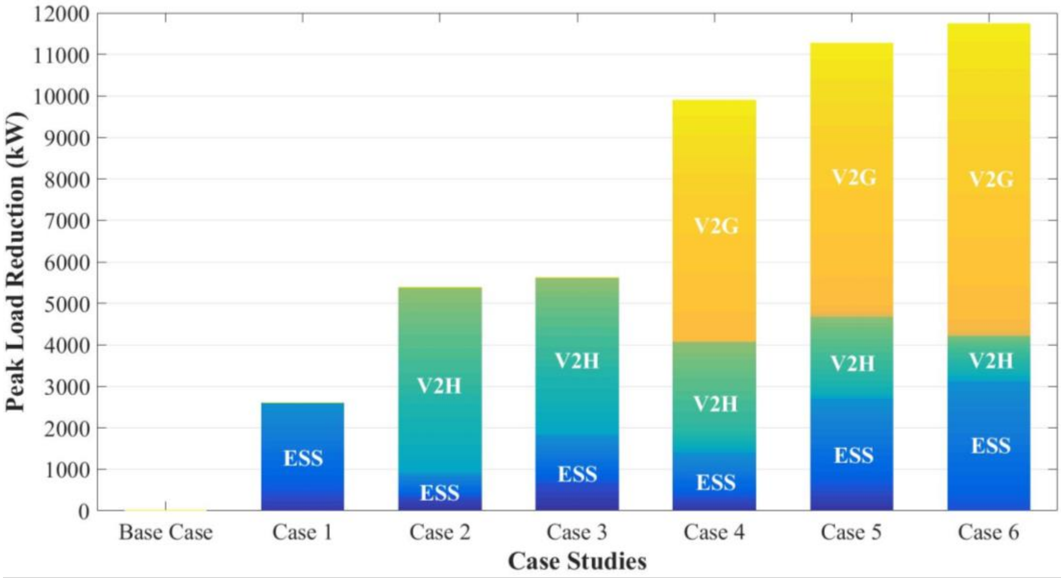

Figure 4.12. PLR values for each of cases during DR event.

Table 4.4. Comparison of the considered case studies

Case Studies	Purchased Energy [kWh]	Sold Energy [kWh]	PLR [MW]	Battery Degradation Cost [¢]	Total Energy Cost [¢]
Base Case	2648.11	--	--	--	17360.1
Case 1	2392.83	367.01	2.60	--	12434.5
Case 2	2453.11	352.73	5.39	836.30	11818.9
Case 3	2388.92	290.89	5.63	710.21	11652.9
Case 4	2938.47	863.75	9.89	1579.15	10238.6
Case 5	2913.27	868.16	11.26	1594.06	9734.9
Case 6	2942.50	857.91	11.74	1602.30	9473.9

4.2 Optimal Management of Mobile Charging Stations in Urban Areas in A Distribution Network

4.2.1 Input data

In this study, real-world charging profiles with 10-minute resolutions are employed to make a realistic analysis by taking into account the behavior of EV users. The raw dataset consists of 348 plug-in EV charging profiles in 2009 from the Midwest region of the United States (Muratori et al. 2013; Muratori, 2017). The raw dataset was processed using MATLAB *cftool* to obtain most appropriate distribution function.

To accomplish this, several distribution functions are tested for 50 different charging demands, Gaussian distribution is found to be the most appropriate based on fitting performance indices as SSE: 1,087, R-square: 0,9571, Adjusted R-square: 0,9499, RMSE: 0.301. Thus, the time window determined for the charging demands of the EV users is realistically modeled.

On the other hand, the EV battery capacities used in the study were randomly selected among the commercially available EVs given in Table 4.5, using the normal distribution method. The mean and standard deviation values were defined as $\mu = 47{,}68$ and $\sigma = 13{,}96$, respectively. Finally, demand locations were randomly determined with changing intensity rate, using a cartesian coordinate system and a city plan, as illustrated in Figure 3.2.

In order to more clearly demonstrate the economic benefits of the proposed system, it is assumed that wind power plants are deployed near the city. The statistics for wind power plants is based on data from 2022 for the Texas region of the United States (Anonym, 2022).

Figure 4.13 depicts the hourly energy production of wind farms and energy demand in the Texas region on the first week of April. The energy production of wind power plants climbs between 3:00 and 8:00 whereas energy demand falls during the same time period, as seen in Figure 4.13.

Table 4.5. Electrical characteristics of electric vehicles

EV Type	Battery Cap. [kWh]	EV Type	Battery Cap. [kWh]
BMW i-3	38	Tesla Model 3	75
Hyundai Kona	64	Kia E-Niro	64
Mini Cooper Se	29	Audi Q4 E-Tron	76
Renault Megane E-Tech	40	Hyundai Kona Limited	39
Renault Zoe	52	Peugeot e-208	45

This implies that the electricity price may decrease between the specified hours in the dynamic pricing environment. Hence, in Case 3, the energy price is rearranged for this period and an economic comparison is made with the other cases. As a result, the real-time electricity purchasing and selling prices were adapted from (Taşcıkaraoğlu, 2018) and rearranged electricity purchasing/selling price are shown in Figure 4.14.

Besides, it should be stated that the optimization problem is solved using General Algebraic Modeling System (GAMS) v.25.1.3 software and solver CPLEX 12.9. It takes 4.83s, 6043s and 18612.1s for Cases 1, 2 and 3, respectively to solve the mixed integer problem using a quad core laptop with 2.5 GHz CPU and 8 GB RAM. When considering the high time resolution (5-min) and number of charging locations, it can be stated that the computational times are reasonable (Cui et al., 2018).

4.2.2 Simulation and results

A mobile charging station can basically be defined as a truck that carries a high-capacity battery pack, a control unit and charging plugs. Charging specifications of MCSs are given Table 4.6. It is assumed that MCSs which have 200kWh battery pack are denoted with AC and DC 44kW chargers. Because of the on-board charger limitations of EVs, MCSs can discharge with maximum 22 kW power while can charge a power of 44 kW.

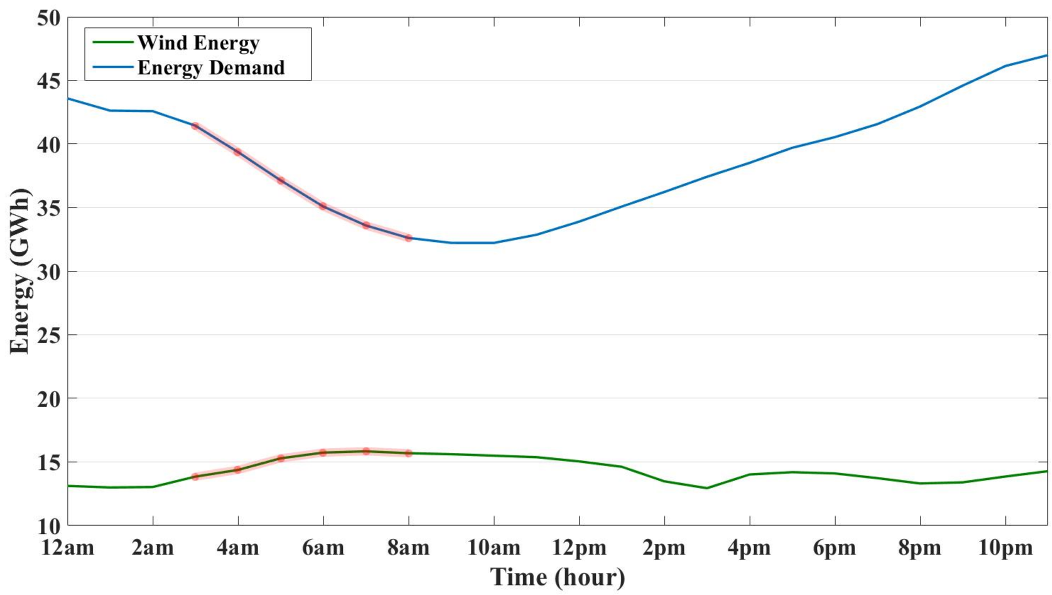

Figure 4.13. Wind energy production and energy demand exchange in Texas, USA.

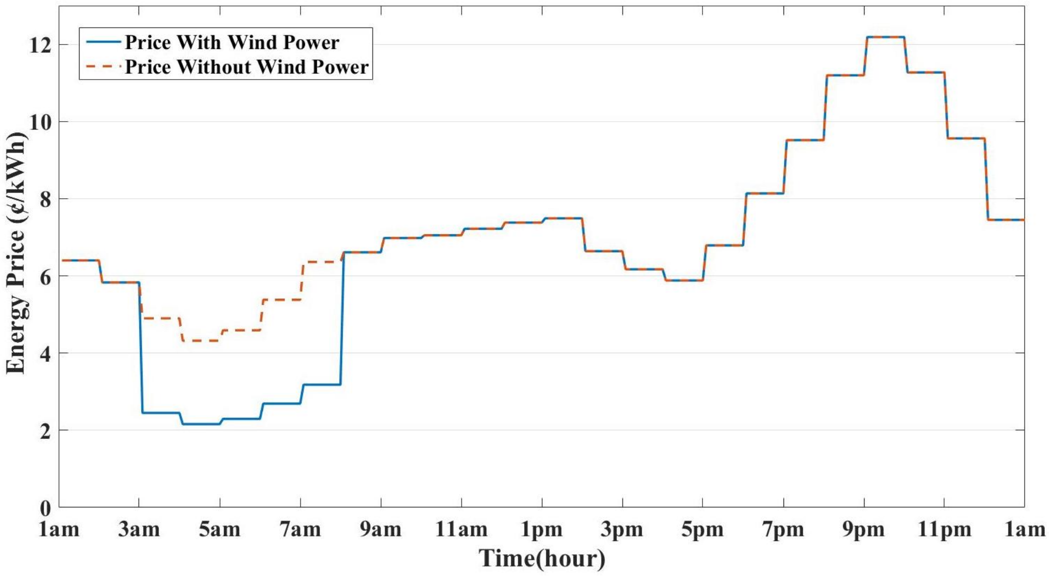

Figure 4.14. Price variation in a one-day test period.

Table 4.6. Specifications of the mobile charging stations

Case Studies	Charging rate [kW]	Discharging rate [kW]	Charging/ Discharging Efficiency	Charging Service Start Time
Case 1&2	44	22	0.98	7:00
Case 3	44	22	0.98	8:00

In order to evaluate the effectiveness of the proposed system, three cases are defined as follow:

- Case 1: Two MCS are employed into the system.
- Case 2: Five MCS are employed into the system.
- Case 3: Five MCS and a wind power plant are employed into the system.

First, in order to show the potential benefits of proposed system, only 2 MCS are considered in Case 1. For Case 1, eight different charging demand created randomly from EV spatial-temporal datasets. In a similar vein, 19 different charging demand created for Cases 2 and 3.

In Case 1, because the number of MCS is less, it can only accept a small number of charging requests, resulting in a low total profit for the system. The number of charge requests responded to increase in direct proportion to the growing number of MCS in Cases 2 and 3.

In order to provide a clear representation in the energy and power figures, Case 1 is neglected. The SoE variations for Cases 2 and 3 are shown in Figure 4.15 based on both the total and one specific MCS. The time difference between the case studies is around one hour, as shown in the figure. This is due to the fact that the service start time is postponed by one hour in Case 3 to maximize the utilization of wind energy. Furthermore, although the same charge demand data is used in both cases, the response of MCSs for charging service changes based on the optimization algorithm to minimize the system operation cost.

As can be seen from Figure 4.16, MCSs can be fast charged because of their high charging power. The optimization algorithm aims to minimize the system operation cost by selecting a time period for the charging process of MCSs when the wind energy is high and the energy demand is low.

Besides, the peak level of total discharge power has remained lower since the allowed discharge power is less than the charging power and the demands are distributed over a longer time period. On the other hand, Figure 4.17 depicts the operation of MCSs during charging service for Case 2. Traveling routes can be intricate, as seen in Figure 4.17, because the parameters such as time window, distance and SoE level are taken into account together when creating the MCS route.

The comparison of the main results for the cases is given in Table 4.7. The purchased energy from the grid is the sum of the sold energy to the EVs and the consumed energy on the road. The purchased and sold energy increases for Cases 2 and 3 compared to Case 1 while the total operation cost decreases. Since Cases 2 and 3 have the same number of MCSs and charging requests of EVs, the amounts of energy purchased and sold in both cases are considerably near to each other. However, because the wind power plant is integrated into the power grid, the total operation cost decreases for Case 3 compared to Case 2.

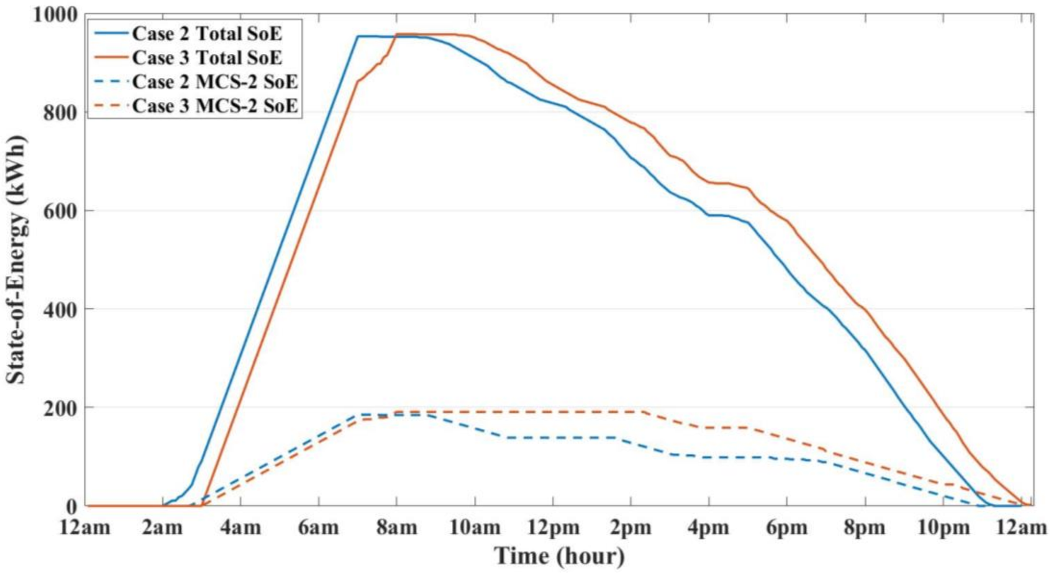

Figure 4.15. SoE variation of MCSs for Case 2 and 3 in a one-day test period.

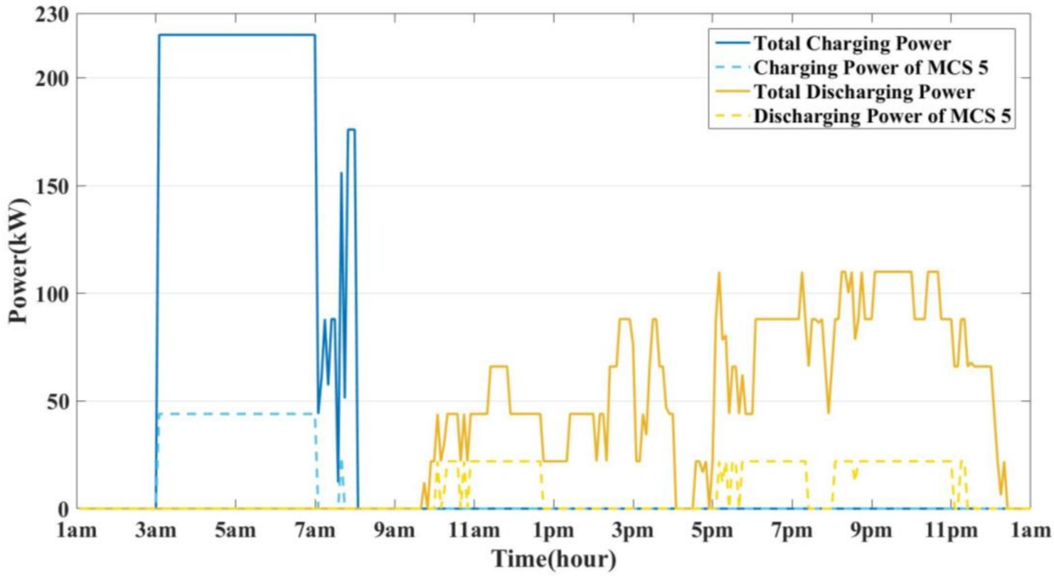

Figure 4.16. Power exchanges of MCSs for Case 3 in a one-day test period.

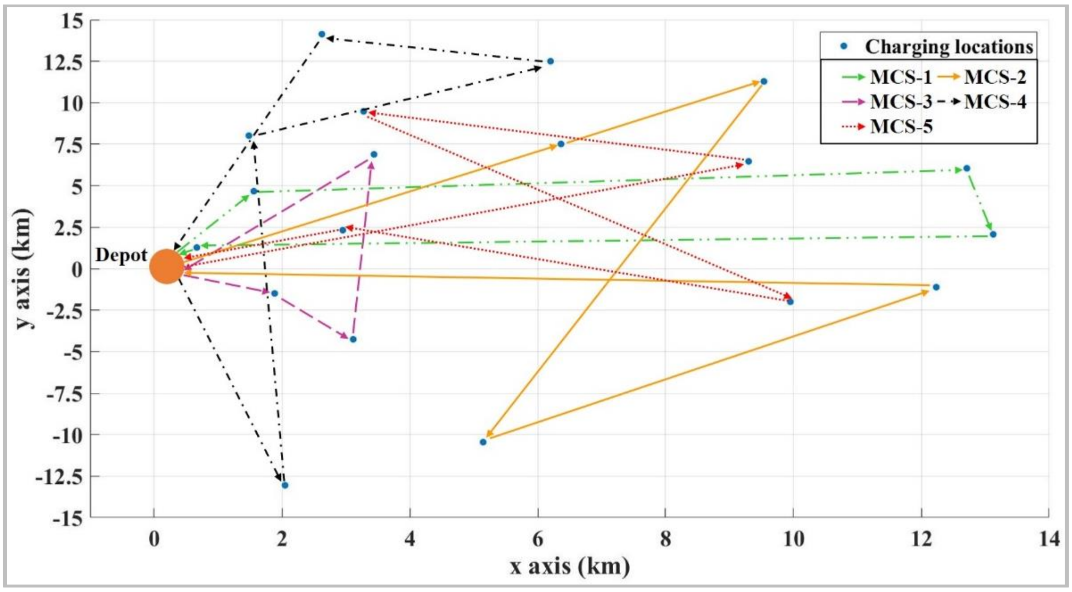

Figure 4.17. Travelling of MCSs between charging locations in Case 2.

Table 4.7. Comparison of the considered case studies

Case Studies	Purchased Energy [kWh]	Sold Energy [kWh]	Total Operation Cost [¢]
Case 1	198.85	186.1	-1187.3
Case 2	973.15	906.3	-3180.0
Case 3	977.83	906.3	-5782.3

5. CONCLUSIONS

The integration of new energy management methods into power system operation is crucial in order to address the operational challenges brought on by the deployment of new generation of electric loads with high power and energy values into power grids. In this thesis, a comprehensive research about the energy management of two different operations -neighborhood composed of residential end-users, and MCSs responsible for EV charging- is presented. Utilizing RESs, a shared ESS, EVs, and MCSs, these two novel energy management approaches have been developed in a linear programming framework with the aim of improving the flexibility and reliability of the power system operation as well as providing financial benefits to the end-users or LSE.

In the first method, an energy management strategy including ECM and PLR-based DR program was implemented in a microgrid environment to reduce the energy cost of the end-users and decrease the peak load demand on the power grid. Energy credits gained by the end-users via excess renewable energy or via the current SoE level of their EV at the arrival time are used during the peak periods through the shared ESS or V2G/V2H services. Therefore, in consideration of the dynamic pricing tariff, both the houses and LSE obtain significant advantages by using these services.

A set of case studies was tested to reveal the effectiveness of the proposed algorithm. The results obtained show that the proposed method reduces the TEC of the neighborhood by 43.9% and 21.7% for the Base Case and Case 1, respectively when compared to the cases without V2G/V2H services. Besides, it reduces the TEC by 17.6% and 16.5% for Case 2 and Case 3, respectively, when compared to the cases without V2G service. Furthermore, while the proposed case reduces the TEC by 4.92% when compared to Case 4, it only increases the TEC by 2.68% compared to Case 6. It should be indicated for the proposed case that the peak loading in the neighborhood area during the DR period decreases 78.7%, 62.1%, 32.9% and 25.8% in comparison with the Base Case, Cases 1, 4 and 6, respectively. Although the proposed case performs worse than Case 2 and 3 in reducing the peak loading in the neighborhood, it performs better in terms of the total PLR.

As a result of the conducted analyses, it can be concluded that the implementation of EVs with V2G and V2H technologies into a microgrid enables the economic and technical benefits for the LSE and end-users. It is clear that, in a case implementing multiple microgrids composed of numerous end-users with greater EVCS capacity, more substantial advantages can be achieved.

In the second method, a spatial-temporal energy management approach based on the routing problem for multiple MCSs is presented in this study in order to reduce the charging costs of EVs. Different types of EVs and various charging demands based on Gaussian distribution are considered for three cases with different numbers of MCS. Besides, the effect of the integration of wind power is evaluated on the performance of the proposed approach. Finally, the economic comparisons show that the proposed method reduces operating cost by 79.5% and 45%, respectively, compared to Case 1 and 2. The results obtain validate that the spatio-temporal approach can effectively reduce the charging costs while satisfying the EV charging demands.

As a future direction, the applicability and effectiveness of the proposed approaches can be examined on a larger scale by considering multiple microgrids, a high number of MCSs, uncertainty of renewable production and energy prices. Besides, the optimal bidding strategies can be developed to increase the benefits of the proposed energy management approaches by integrating new constraints such as day-ahead and real-time market operations or a certain PLR level imposed by LSE.

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Work Experience

Year	Company	Position
2020 - 2021	BEST Transformer	Test Engineer
2021 -	Muğla Sıtkı Koçman University	Research Assistant

Foreign Language

English	Beginner	Intermediate	Advanced
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Speaking			x
Listening			x
Reading			x

Publications:

- Beyazit, Muhammed Ali, and Akin Tascikaraoglu. 2022. "Optimal Management of Mobile Charging Stations in Urban Areas in a Distribution Network." 1–6. doi: 10.1109/sest53650.2022.9898420.

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Hobbies

1. Playing football
2. Swimming
3. Watching film