ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

AN AGENT-BASED ENERGY MANAGEMENT APPROACH FOR V2X-CAPABLE CHARGER CLUSTERS

M.Sc. THESIS

Gülen AKYÜN

Department of Electrical Engineering

Electrical Engineering Programme

JANUARY 2023

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V2X ÖZELLİKLİ ŞARJ KÜMELERİ İÇİN ETMEN-TABANLI ENERJİ YÖNETİM YAKLAŞIMI

YÜKSEK LİSANS TEZİ

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Gülen AKYÜN, a M.Sc. student of ITU Graduate School student ID 504191071 successfully defended the thesis entitled “AN AGENT-BASED ENERGY MANAGEMENT APPROACH FOR V2X-CAPABLE CHARGER CLUSTERS”, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my family,

FOREWORD

I would like to thank my thesis advisor Assoc. Prof. Dr. Murat YILMAZ at Istanbul Technical University, for all the support and valuable advice. He has supported me since my undergraduate education. Also, I would like to present my greatest gratitude to M.Sc Erdem GÜMRÜKÇÜ at RWTH Aachen, for his encouragement and support. Thanks for your valuable time and for guiding me. Finally, I would like to thank my dear parents and my brother for always being there for me.

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ABBREVIATIONS

AEV	: All-electric Vehicle
BEV	: Battery Electric Vehicle
CHP	: Combined Heat and Power
CPPS	: Cyber-physical Power System
CU	: Charger Unit
DER	: Distributed Energy Resource
DF	: Directory Facilitator
DG	: Distributed Generation
DSM	: Demand Side Management
DSO	: Distribution System Operator
EMS	: Energy Management System
EPS	: Electric Power System
EV	: Electric Vehicle
EVGI	: Electric Vehicle-Grid Integration
FCEV	: Fuel Cell Electric Vehicle
FIPA	: Intelligent Physical Agents Foundation
G2V	: Grid-to-Vehicle
GEV	: Gridable Electric Vehicles
HEV	: Hybrid Electric Vehicle
HP	: Heat Pumps
IEC	: International Electrotechnical Commission
IEEE	: Institute of Electrical and Electronics Engineers
ISO	: International Organization for Standardization
MAS	: Multi-agent System
PEV	: Plug-in Electric Vehicle
PHEV	: Plug-in Hybrid Electric Vehicle
PV	: Photovoltaic
RES	: Renewable Energy Sources
SAE	: Society of Automotive Engineers
SOC	: State of Charge
THD	: Total Harmonic Distortion
TSO	: Transmission System Operator
UL	: Underwriters Laboratories
V2B	: Vehicle-to-Building
V2G	: Vehicle-to-Grid
V2H	: Vehicle-to-Home
V2V	: Vehicle-to-Vehicle
V2X	: Vehicle-to-Everything
WAVE	: Wireless Access in Vehicular Environments
WEC	: Wind Energy Converters
WPT	: Wireless Power Transfer

SYMBOLS

E	:	Energy
m(t)	:	Tolerance value at time t
$\mathbf{m_{\delta}}$	:	Tolerance threshold
P	:	Power
$\mathbf{P_p}$	:	Power provided by producer
$\mathbf{P_{ch}}$	:	Charger Power
$\mathbf{P_c}$	:	Power demanded by consumer
SOC(t)	:	Value of SOC at time t
$\mathbf{SOC(t_D)}$	:	Target SOC at departure time
$\mathbf{SOC_c(t_1)}$	:	Value of SOC at time t_1
$\mathbf{SOC_c(t_2)}$	:	Value of SOC at time t_2
t	:	Time
$\mathbf{t_D}$	:	Departure time

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AN AGENT-BASED ENERGY MANAGEMENT APPROACH FOR V2X-CAPABLE CHARGER CLUSTERS

SUMMARY

To deal with the intermittency problem of renewable-based distributed generation, flexible energy assets such as electrical batteries are widely considered. In line with the localization trend in the energy sector, electric mobility is becoming mainstream. The additional load demand that comes with the penetration of EVs will raise the need for additional electricity generation. In particular, aggregated charging load of electric vehicles cause overload in the distribution network. With the management of EV charging, overload can be avoided and grid reliability can be ensured. At this point, smart grid applications promise to help make the addition of electric vehicles to the grid more sustainable with concepts such as V2X (vehicle to everything). On the other hand, as the plug-in EV fleet grows, an effective energy management system is needed to avoid adverse effects such as voltage fluctuations and increased electricity losses. By combining several flexible energy assets, a bidirectional EV charger cluster can have a local balancing capacity and therefore be operated without demanding energy from the grid for a specified period of time. The aim of this thesis is to manage EV charging in clustered systems and to obtain energy neutral charger clusters by increasing the local balancing capabilities of clusters and to efficiently use V2X functions with the proposed energy management algorithm. With this thesis, it is also aimed to reduce the peak-to-average ratio and to provide a balanced and efficient load profile. To achieve the objectives, an agent-based energy management concept has been proposed. In the proposed concept, each bidirectional charging unit with a connected EV at the charging station is represented by an agent. This approach provides a decentralized structure and swarm control in line with the agents' local targets. In this algorithm all power producers and consumers are represented as agents. First, the agents calculate their operation range and current power demand or production, i.e. their flexibility. Energy consumers and producers then interact and negotiate with each other, thus providing self-consumption by meeting each power consumption with an equivalent power generation. This allows flexible power transfer between EVs with a collaborative perspective on the charging system. In this way, the peak-to-average ratio decreases and self-consumption increases. In the study, the negotiation and decision-making processes of the agencies are discussed in detail. Simulation studies performed on the proposed concept for local balancing show that this application has the potential to provide effective and sustainable solutions for energy management.

V2X ÖZELLİKLİ ŞARJ KÜMELERİ İÇİN ETMEN-TABANLI ENERJİ YÖNETİM YAKLAŞIMI

ÖZET

Yenilenebilir tabanlı dağıtık elektrik üretiminin kesinti sorunuyla başa çıkmak için, piller gibi esnek enerji kaynakları dikkate alınmaktadır. Enerji sektöründeki yerelleşme eğilimine paralel olarak, elektrikli ulaşım yaygın hale gelmektedir. Elektrikli araçların (EA'ların) yaygınlaşmasıyla ortaya çıkan ek yük talebi ise ek elektrik üretimi ihtiyacını arttırmaktadır. Özellikle elektrikli araçların toplu halde şarj talebi, dağıtım şebekesinde aşırı yüklenmeye neden olacaktır. EA şarjının yönetimi ile aşırı yüklenme önlenebilir ve şebeke güvenilirliği sağlanabilir. Bu noktada akıllı şebeke uygulamaları, araçtan herşeye (V2X) gibi kavramlarla şebekeye elektrikli araçların eklenmesini daha sürdürülebilir hale getirmeye yardımcı olmayı vaat etmektedir. Öte yandan, şarj edilebilir EA filosu büyüdükçe, voltaj dalgalanmaları ve artan elektrik kayıpları gibi olumsuz etkilerden kaçınmak için etkin bir enerji yönetim sistemine ihtiyaç duyulmaktadır. Birkaç esnek enerji kaynağını bir araya getirerek, bir çift yönlü EA şarj ünitesi kümesi, yerel bir dengeleme kapasitesine sahip olabilir ve böylece belirli bir süre için şebekeden enerji talep edilmeden çalıştırılabilir.

Yenilenebilir enerji gibi yeni nesil enerji kaynakları ve EA gibi depolama sistemleri ile şebekedeki birçok elemanın enerji akışlarını izlemek ve kontrol etmek için bir enerji yönetim sistemine (EMS) ihtiyaç duyulmaktadır. Bir EMS, enerji kaynakları arasındaki enerji akışını koordine ederek güç sisteminin arz-talep dengesinin korunmasına yardımcı olurken, maliyeti en aza indirmeyi amaçlar. EA şarj kümeleri için EMS hedefleri belirlenirken, ekonomik, çevresel veya teknik faktörlerin yanı sıra kullanıcı çıkarları da dikkate alınır. Sosyo-ekonomik temelli bu yaklaşımlar belirlenirken, kontrol yönteminin mimari yapısı belirlenir ve pik yükün en aza indirilmesi veya yük profilinin düzleştirilmesi gibi amaçlara dayalı olarak algoritmalar geliştirilir. EMS'lerin operasyonları genellikle bu kontrol mimarilerine bağlıdır ve merkezi ve merkezi olmayan olarak ayrılabilir.

Merkezi EMS yaklaşımında, merkezi yüksek performanslı bilgi işlem birimi, EA şarjını koordine etmek için şebekeden ve EA'lardan veri toplar ve buna göre küresel bir optimizasyon sağlar. Merkezi olmayan kontrol mimarisinde, merkezi kontrol mimarisinden farklı olarak, her yerel birim kendi stratejik planını oluşturur ve diğer yerel birimlerle iletişim kurar. Merkezi birim, bu planları bir araya getirme rolüne sahip olabilir, ancak karar verme yetkisine sahip olmaz. Bu sayede EA kullanıcılarının parametreleri ve optimizasyon kriterlerine göre EA şarj süresi belirlenir ve şarj maliyeti minimize edilir. Aşağıdan yukarıya yaklaşım olarak da adlandırılan merkezi olmayan EMS, sunduğu çalışma esnekliği nedeniyle genişletilebilir. Bu özelliği, merkezi olmayan yaklaşımı büyük ölçekli uygulamalarda merkezi mimariden üstün kılar. Ayrıca hesaplama yükü ve hızlı yanıt açısından merkezi EMS'den üstündür.

Merkezi ve merkezi olmayan mimarinin avantajlarını birleştiren bir yapı, hiyerarşik tabanlı kontrol mimarisi olarak adlandırılır. Bu yapıda yerel kontrolörler ve bunlara bilgi sağlayan merkezi bir birim bulunmaktadır. Aslında hiyerarşik koordinasyon, birçok dolaylı ve doğrudan toplayıcıyı bir araya getirererek oluşturduğu yapıları nedeniyle tam merkezi veya merkezi olmayan olarak sınıflandırılamaz.

EA penetrasyonu arttıkça, EA'ların öngörülemeyen davranışı nedeniyle güç talebi yönetimi daha zor hale gelecektir. Bir EA filosundaki şarj süreçlerini temsil edebilecek daha etkili bir modele ihtiyaç vardır. Etmen tabanlı yaklaşım veya çok etmenli sistem (MAS), dağıtık veya hiyerarşik koordinasyon altında da sınıflandırılabilen alternatif bir tekniktir. MAS, küresel ortak bir hedefe ulaşmak için iki veya daha fazla etmenin kendi yerel hedeflerini gerçekleştirdiği bir sistemdir. Esnekliği ve genişletilebilirliği nedeniyle, bu yaklaşım dağıtım ağı uygulamalarında ve dağıtık enerji kaynaklarında (DER'lerde) giderek daha fazla kullanılmaktadır. DER'lerin akıllı kontrolü ve enerji yönetimi için umut verici bir yöntem olarak görülen MAS, birçok karmaşıklığı da beraberinde getirmektedir. Sistem davranışı tüm etmenlerin davranışlarından kaynaklandığından, büyük ölçekli sistemlerde davranışı tahmin etmek zor olabilir. Etmen sayısındaki artışla birlikte iletişim karmaşıklığındaki artış kaçınılmaz olacaktır. Buna bir çözüm olarak, holonik MAS adı verilen tamamen dağıtılmış ve hiyerarşik bir kontrole dayanan SwarmGrid-X konsepti ortaya çıkmıştır. Bu yaklaşımda etmenler, yerel çevreyi algılayan ve kendi yerel kararlarını organize eden bir dizi davranış sergilerler.

Bu tezde, kümelenmiş sistemlerde EA şarjını yönetmek ve kümelerin yerel dengeleme yeteneklerini artırarak enerji-nötr şarj kümeleri elde etmek için bir enerji yönetimi yaklaşımı önerilmektedir. Önerilen yaklaşım ile V2X işlevlerini verimli bir şekilde kullanarak tepe-ortalama oranının düşürülmesi ve dengeli ve verimli bir yük profili sağlanması amaçlanmaktadır. Bu amaçlar doğrultusunda, etmen tabanlı bir enerji yönetimi yaklaşımı önerilmiştir. Önerilen konseptte, şarj istasyonundaki elektrikli araçlara bağlı her bir çift yönlü şarj ünitesi, bir etmen (agent) tarafından temsil edilmektedir. Bu yaklaşım, merkezi olmayan bir yapı ile etmenlerin yerel hedefleri doğrultusunda bir sürü kontrolü sağlar. Bu yaklaşımda tüm güç üreticileri ve tüketiciler etmenler tarafından temsil edilmektedir. İlk olarak, etmenler çalışma aralıklarını hesaplar ve mevcut güç taleplerini veya üretimlerini yani esnekliklerini ortaya çıkarır. Enerji tüketicileri ve üreticileri daha sonra birbirleriyle etkileşime girerek pazarlık yapar, böylece her güç tüketimini eşdeğer bir güç üretimi ile karşılayarak küme içerisinde öz tüketim sağlanır. Bu, şarj sisteminde işbirlikçi bir bakış açısıyla elektrikli araçlar arasında esnek güç aktarımına izin verir. Bu şekilde, tepe-ortalama oranı azalır ve küme içerisindeki tüketim ihtiyacı karşılanabilir.

Bu tez kapsamında önerilen enerji yönetimi konsepti, SwarmGrid-X algoritmasının değiştirilmiş bir versiyonuna ve tüketici-üretici aracıları arasında bir anlaşma protokolüne dayanmaktadır. Bu konsept, elektrikli araç şarj istasyonunun merkezi olmayan kontrolünü sağlar. Bu tezde uygulanan senaryolarda, önceki Swarm-Grid uygulamalarından farklı olarak şarj üniteleri çift yönlüdür. Yani hem araçtan şebekeye hem de şebekeden araca şarj işlemi yapılabilmektedir. Bu, sistemdeki şarj ünitelerinin hem şarj hem de deşarj olabileceği anlamına gelir. Ayrıca şarj ünitelerine bağlı EA'ların talep profilleri önceki senaryolarda aynı iken, bu tezde ele alınan senaryolarda

EA'lerin şarj talepleri heterojen ve dolayısıyla şarj talep profilleri ve araçların esnekliği değişkendir. Bu nedenle, bu tezde, SwarmGrid-X algoritması bu ihtiyaçlara göre değiştirilmiş ve kümelenmiş EA filo enerji yönetiminin taleplerine uyarlanmıştır. Tez kapsamında odaklanılan hedef, önerilen enerji yönetimi algoritması ile V2X işlevlerini verimli bir şekilde kullanmak ve kümelerin ve sistemin tepe/ortalama güç oranını azaltmaktır. Bu çalışma ile şebeke operatörlerine ve EA kullanıcılarına kolaylık sağlanmasının yanı sıra çevresel ve ekonomik katkılar sağlanması hedeflenmektedir. Tepe güç talebinin azaltılması dengeli ve verimli bir yük profili sağlayacak ve bu da şebeke kalitesini iyileştirecektir. Tez kapsamında etmenlerin müzakere süreçleri ve karar verme süreçleri ile optimum çözüme ulaşma süreçleri detaylı olarak ele alınmıştır. Yerel dengeleme için önerilen konsept üzerinde gerçekleştirilen simülasyon çalışmaları, bu uygulamanın enerji yönetimi için etkili ve sürdürülebilir çözüm sunma potansiyeline sahip olduğunu göstermektedir.

1. INTRODUCTION

Every day, governments are setting various and ambitious targets to be energy efficient and reduce emissions of harmful substances. One of the key players in the focus of all these goals is electric vehicles (EVs), which are promising in creating a cleaner environment. The main reason behind this is that it has been determined that at least 10 % of the emissions originate from transportation and especially road transportation has a significant share among them [1]. Accordingly, by 2021, more than 20 countries have committed to a complete cessation of sales of road vehicles with internal combustion engine (ICE) within the next 30 years [2]. The trend towards electrical transportation in order to reduce greenhouse gas emissions from transportation continues to increase in recent years. The fact that global Plug-in Electric Vehicle (PEV) sales reached 7 million in 2021 clearly shows increasing interest in EVs [3].

In road transportation, the energy source used is rapidly shifting from petroleum to electrical energy. At first, EVs were considered suitable for use over short distances in the city, due to their low range and slow charging speed. However, with the development of battery technologies and the increase in the power capacity of chargers, EVs have begun to replace ICE vehicles [4]. Electric vehicle technology, which stands out as a sustainable solution for reducing greenhouse gas emissions, brings some challenges with it.

PEVs, one of the EV types, are charged from the grid. It is anticipated that increased PEV penetration will affect load profiles and cause difficulties in the grid. One of the most important challenges in electrification of vehicles is the unpreparedness of the charging infrastructure and grid. Possible problems such as voltage imbalance, overload, power losses, frequency variation, harmonics, which are the effects of increasing power demand on the local distribution grid due to the increase in EVs, are discussed in the literature [5].

The additional load demand introduced by the integration of EVs will raise the need for additional electricity generation. In particular, aggregated charging load of EVs will cause overloading on distribution grid. The future of electromobility depends on the development of charging technology and charging infrastructure. Smart charging can ease the problems caused by overloading, help ensuring grid reliability and improve energy economy [6]. Smart charging is basically the control of charging in line with certain goals such as reducing charging costs, minimizing power loss or avoiding overload on the grid [7]. Uncontrolled charging of EVs may increase peak loads in the best-case scenario and compromise the reliability and stability of the power system in the worst-case scenario. Even simple solutions such as shifting the charging periods of low energy demand using the flexibility of EVs can be enough to reduce the peak load. Thus, at the same time, the valleys in the load profile, that is, the times that indicate the times when the energy demand is lower, can be also filled and the load profile becomes flat [8].

1.1 Purpose of Thesis

The aim of this thesis is to manage EV charging in clustered systems and to provide power neutralization as much as possible within a cluster of EVs. In order to achieve this, an agent-based energy management concept has been proposed. In the proposed concept, each bidirectional charging unit (CU) with a connected EV in the charging station is represented by an agent. Depending on the flexibility of the charging demand of the connected EV, each agent takes the role of producer or consumer. Producer and consumer agents negotiate directly with each other for the power demand and supply, without the supervision of any central authority. According to the agreement between the agents after the negotiation, the batteries of the EVs represented by producer agents, are discharged for a certain period of time to charge another (or more) vehicle as a power source. Consumer agents try to meet their demands as much as possible from the producer agent in the cluster.

This energy management concept is based on a modified version of SwarmGrid-X algorithm and a negotiation protocol between consumer-producer agents. This concept enables decentralized control of electric vehicle charging station. Unlike previous

Swarm-Grid applications, the charging units are bidirectional in the scenarios applied in this thesis. In other words, charging can be carried out both from the vehicle to the grid and from the grid to the vehicle. This means that the charging units in the system can both charge and discharge. In addition, while the demand profiles of EVs connected to the charging units were identical in the previous scenarios, the charging demands of EVs are heterogenous in the scenarios considered in this thesis, and therefore the profiles of the charging demand and the flexibility of the vehicles are diverse. Therefore, in this thesis, the swarm-grid-X algorithm has been modified according to these needs and adapted to the demands of clustered EV fleet energy management.

The goal focused in this study is to use the vehicle-to-everything functions efficiently and to reduce the peak to average ratio of the clusters and the system, with the proposed energy management algorithm. With this study, it is aimed to provide convenience to grid operators and EV users, as well as environmental and economic contributions. Reducing the peak power will provide a balanced and efficient load profile and this will improve the grid quality.

1.2 Literature Review

In the literature, EV charging strategies are classified as scheduling, clustering and forecasting, according to the problem they focus on in order to control high EV penetration and reduce their effects on the local distribution grid. A scheduling strategy generally aims to reduce the peak problems by shifting the demand, it can be divided into two as centralized and decentralized. Clustering strategy is used to group repetitive load profiles according to time intervals of various consumption behaviors (home, workplace, etc.) in a dataset and is based on methods such as Markov-inspired stochastic, k-means, self-organizing maps [9]. Finally, one of the challenges in controlling EV charging is the high uncertainty EVs have. There is uncertainty about many factors such as the arrival and departure times of the EVs at the charging station, the state of charge (SOC) of the battery, the charging preferences, the demand of other EVs, the current state of the electricity grid. Short, medium and long-term precision forecasting strategies are used to address the uncertainties of EV charging. Studies present many approaches to control EV charging, but the approaches have shortcomings in real applications in terms of their functionality and performance.

Although the structure of conventional electrical power systems is defined by a hierarchical transmission from large power generators to distribution networks and from there to the consumer, today this concept is changing with local generators and storage systems. This power system concept, where consumers can also be local producers, is called distributed generation (DG). This change, which has been going on for the last 25 years, has been one of the most interesting concepts for both energy consumers, power system operators and energy policy developers [10]. On the other hand, the concept of demand-side management (DSM) has emerged to accelerate the energy transition, reduce consumer bills and reduce fossil fuel energy use. DSM has become important especially in order to balance the peak power demand and meet the increasing energy demand efficiently. DSM aims to try to minimize the difference between maximum and minimum power consumption [11].

The growth of DERs in the energy market, as well as developments in information technology, have led to a shift from traditional centralized power infrastructure to a localized concept. An illustration of comparison between traditional and new energy concept can be seen in Figure 1.1 [12]. Parallel to this, there is a trend towards the creation of an energy distribution network that utilizes various DERs and the smart grid concept [13]. On the other hand, the problems (harmonics, overvoltage etc.) that occur as a result of the intermittent nature of the RES can also be avoided with a well-planned DER. In parallel with the transition to a DER concepts, electrification in transportation also points to EVs that could potentially operate as DER by integrating into the smart grid. PEVs, with their flexible nature, can power the grid as a mobile and distributed energy storage system or source for local loads. EVs, which are considered as flexible energy assets according to their load profiles and energy usage, have been proposed to improve the flexibility of power systems in recent studies [14]. However, there are still very few studies that describe EV user behaviour and the interactions between these flexible assets.

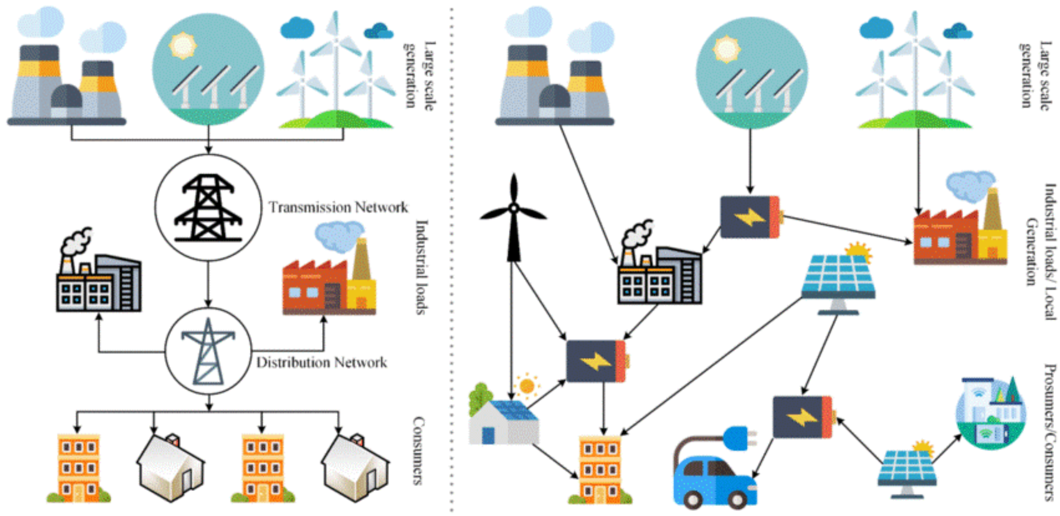

Figure 1.1 : Traditional Energy Concept vs DER Concept [12].

Another concept is V2X, which is proposed to improve grid quality and support the electrical grid by making the best use of the energy storage power of EVs, which are idle without being charged at charging stations 60 % of their time [15]. In this concept EVs can be used not only as a load but also as a storage, making it possible to transfer power from the EV to other assets source by bidirectional charging. In this way, EVs can act as a distributed energy source. By using them as a source in idle times (during parking), peak demand will be reduced. Possible advantages and disadvantages of V2X applications are discussed in detail in the literature [16,17]. Although its disadvantages such as battery degradation, effects on electrical equipment and investment costs cannot be ignored [18], many potential benefits of this technology such as load balancing, peak shaving, correction of harmonics, valley filling, support to RES are promising [19]. It is possible to benefit from V2X operations with the integration of EVs into local power systems. In this way, local power balancing will be possible thanks to the storage feature of EVs in renewable energy power systems. While some studies highlight the challenges of the V2X [20], some surveys explore EV user interest in it [21]. In addition, standardization efforts on this subject show that V2X is a promising technology [22]. Some benefits of V2X for production, distribution and consumer are shown in Figure 1.2 [19] .

With the new generation energy sources such as renewable energy and storage systems such as PEV, an EMS is required to monitor and control the energy flows of many

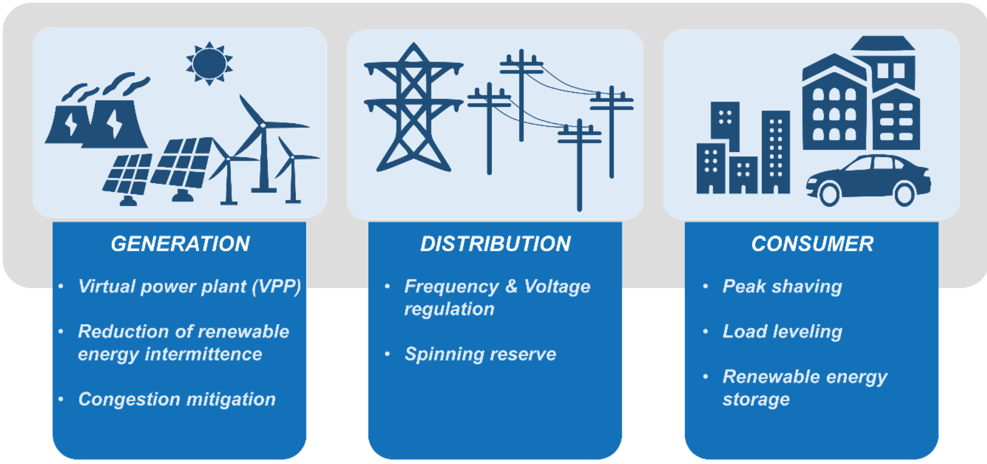

Figure 1.2 : V2X Benefits for Production, Distribution and the Consumer [19].

elements in the grid. In this way, the reliability of the power system is increased while ensuring that the demands of the loads are constantly met [23]. According to the definition of International Electrotechnical commission standard IEC 61970-2, EMS is "a computer system comprising a software platform providing essential support services and a set of applications providing the functionality needed for the effective operation of electrical generation and transmission facilities to assure adequate security of energy supply at minimum cost" [24]. An EMS aims to minimize the cost while helping to maintain the supply-demand balance of the power system by coordinating the energy flow between energy sources.

Solution approaches for EMS can be classified as exact optimization and approximate optimization. Exact approaches are the solution approaches that find the optimum solution in the most sensitive way. Approximate optimization finds solutions close to the optimum. Although exact optimization methods guarantee an optimal solution, they also bring with them computational complexity. However, approximate optimization methods can reach an approximate result relatively faster. Mathematical programming reaches results in a longer time and has more computational burden compared to heuristic and metaheuristic approach. Heuristic methods, on the other hand, reach an approximate result with less calculation time, but require prior knowledge. Since each system offers different advantages, many approaches have

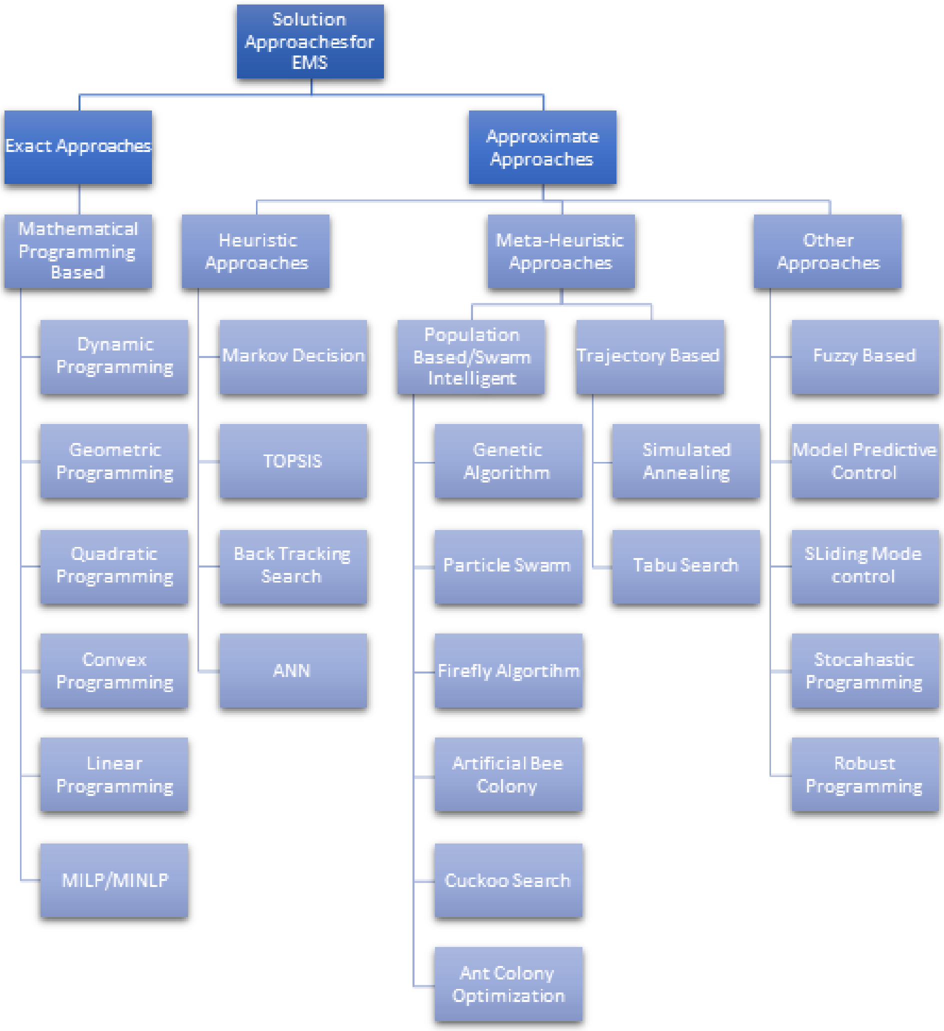

Figure 1.3 : Solution Approaches for EMS [23].

been developed to adapt to the characteristics of the systems and are shown in Figure 1.3 [23].

When setting EMS targets for PEV charger clusters, user interests should be taken into account, as well as economic, environmental or technical factors. While determining these socio-economic-based approaches, the architectural structure of control method is determined and algorithms are developed based on objectives such as minimizing the peak load or flattening the load profile. The operations of EMSs are generally dependent on these control architectures and can be divided as centralized and decentralized. Although the concept of hierarchical EMS is discussed as a third approach in some new sources, this approach is included in distributed EMS in some studies. There are severel studies [5,7,23,25] in which these approaches are discussed and compared in detail.

In the centralized EMS approach, the central high-performance computing unit collects data from the grid and EVs to coordinate EV charging and provides a global optimization accordingly. The centralized architecture is advantageous over the decentralized one in terms of reducing the total operating cost by taking into account all global parameters. On the other hand, since all information is gathered for analysis in a single unit, the computational load increases depending on the number of entities. For central approaches, methods such as two-stage stochastic scheduling [26] are frequently used, which allows the central authority to decide in case of uncertainties. Quan-Do et al. implemented a centralized strategy to minimize the peak load of the grid [27]. Zheng et al. proposed a centralized approach to reduce power fluctuations using genetic algorithm [28].

In the decentralized control architecture, unlike the centralized control architecture, each local unit creates its own strategic plan and communicates with other local units. The central unit may have the role of putting these plans together, but not the decision-making authority. In this way, the EV charging time is determined based on the parameters of the EV users and the optimization criteria, and the charging cost is minimized. The decentralized EMS, also called the bottom-up approach, is extensible due to the flexibility of operation it offers. This makes it superior to centralized architecture in large-scale applications. It is also superior to central EMS in terms of computational load and fast response. In decentralized approaches, methods such as Markov decision process [29] and game theory [30] are used. Wu et al. presented a decentralized structure that controls EV charging and aims to improve EV user satisfaction and pricing [31]. Similarly, Ma et al. proposed a decentralized control structure in which EVs update their load demands iteratively [30]. Gan L. , Topcu U et al, proposed a decentralized algorithm in which each EV updates its charge profile according to the control signal broadcast by the utility [32]. In this way, they aim to achieve valley-filling in load profiles by approaching optimum charging profiles.

A third structure that combines the advantages of centralized and decentralized architecture is referred to as hierarchical-based control architecture in the literature. In this structure, there are local controllers and a central unit that provide information to them. In fact, hierarchical coordination cannot be classified as either fully centralized or decentralized due to its structures created by dividing many indirect and direct aggregators. Thanks to the hierarchical structure, computational requirements can be significantly reduced. Bazmohammadi et al. proposed a hierarchical structure for the energy management of four interconnected microgrids, ultimately minimizing power imbalances while reducing operating costs in 100 separate scenarios [33].

As EV penetration increases, power demand management will become more challenging due to the unpredictable behaviour of EVs. There is a need for an effective model that can represent the charging processes in an EV fleet. Mets and Verschueren aimed to flatten the global load profile with an energy management strategy that requires only the load information acquired via the local load signal and no communication [8]. Although the results promise an improvement in the global load profile, its user-friendliness is debatable. Many studies like [8] on EV charging make an operator responsible for EV charging. However, this approach, which prioritizes the global goals of the operator, does not always take into account the satisfaction of EV users providing V2X services. In contrast, recent publications Yin et al. propose an agent-based scheme that negotiates the decision process assuming each charger has computational capability. Outcomes from agent-based studies show positive results in terms of EV user's benefits [34].

Agent-based approach or multi-agent system (MAS) is an alternative technique under distributed or hierarchical coordination in the literature. MAS is a system where two or more agents achieve their own local goals to achieve a global common goal. Due to its flexibility and extensibility, this approach is increasingly used in distribution network applications and DERs. In the literature review by Ringler et al, agent-based applications within the scope of the smart network were mentioned and the strengths and weaknesses of the studies were discussed in detail [35]. In the literature, MAS for charge control of EV fleets has been used to achieve various objectives such as load balancing and frequency regulation and voltage regulation. Unda et al. aimed to reduce the overloads in the distribution network by using MAS for EV battery charging [36] . Mureddu et al. on the other hand, proposed an agent-based model for both controlling the charging infrastructure in the smart city and predicting electricity supply, as well as managing the charging requirements of the PEV charging fleet [37]. Aljohani et al. proposed a multi-agent hierarchical architecture for dynamic pricing for EV charging in microgrid businesses based on historical data from South Florida [38]. The results show a significant reduction in pricing compared to other methods. Saner et al proposed a hierarchical multi-agent system in which high-level agents send control signals to lower-level agents to reduce demand and energy costs in case of multiple EV charging [39]. Valogianni et al. proposed multi-agent EV charging coordination to bring together the goals of both the interests of EV vehicle owners and grid stability [40]. However, the proposed approach does not support V2X. In [41], an agent-based approach whose simulation is created in the python programming language, controls the EV charging demand of fast charging stations and makes dynamic pricing is presented. In some studies in the literature, EV charging was managed using multi-agent-platforms such as JADE [42] or NETLOGO [43] when modeling multi-agent systems. Seen as a promising method for smart control and energy management of DERs, MAS brings with it many complexities. Predicting behavior in large-scale systems can be a challenge, as system behavior results from the behavior of all its agents. With the increase in the number of agents, the increase in communication complexity will be inevitable. As a solution to this, the SwarmGrid-X concept based on a fully distributed and hierarchical control called holonic MAS was proposed by Dähling et al [44]. Basically, the Swarmgrid-X is an extended version of the Swarmgrid concept proposed by Kolen et al. and its architecture is based on MAS [45]. In this concept, agents display a set of behaviors that perceive the local environment and organize their own local decisions. The agents, who can act as the both consumers and producers, demonstrate their flexibility by calculating the working intervals to achieve their local targets, and interact with each other and negotiate. Agents try to neutralize the power consumption within the community they are in, called the swarm, with the same rate of production. In study [45], simulations on local balancing show that DERs can provide an appropriate and effective energy management and that the algorithm will contribute positively to the participation of DERs in the distribution network.

1.3 Related Standards and Protocols

Related to the charging of electric vehicles, energy management and communication in vehicle-to-grid applications, many organizations such as International Electrotechnical Commission (IEC), Institute of Electrical and Electronics Engineers (IEEE), International Organization for Standardization (ISO), Society of Automotive Engineers (SAE), Underwriters Laboratories (UL) have created various standards. Some of them as follows:

• IEC [24]

- IEC 61850-7-420: Communications systems for Distributed Energy Resources (DER)
- IEC 61980-1: Electric vehicle wireless power transfer (WPT) systems

• IEEE [46]

- IEEE 1547: Interconnecting Distributed Resources with Electric Power Systems
- IEEE 2030: Guide for Smart Grid Interoperability of Energy Technology and Information Technology Operation with the Electric Power System (EPS) and End-Use Applications and Loads
- IEEE 1609: Family of Standards for Wireless Access in Vehicular Environments (WAVE)

• ISO [47]

- ISO 15118 Road vehicles — Vehicle to grid communication interface
- ISO 8714: Electric road vehicles — Reference energy consumption and range
- ISO 17409:Electrically propelled road vehicles — Conductive power transfer

• SAE [48]

- SAE J 1772: Electric Vehicle Conductive Charge Coupler
- SAE J 1773: Electric Vehicle Inductively Coupled Charging
- SAE J 2758: Determination of the Maximum Available Power from a Rechargeable Energy Storage System on a Hybrid Electric Vehicle
- SAE J 2894: Power Quality Requirements for Plug-In Electric Vehicle Chargers

- SAE J 2293: Energy Transfer System for Electric Vehicles

- SAE J3072: Interconnection Requirements for Onboard, Grid Support Inverter Systems

• UL [49]

- UL 2202: Standard for Electric Vehicle (EV) Charging System Equipment

- UL 9741: Bidirectional Electric Vehicle (EV) Charging System Equipment

Standardization of EV components and EV-grid integration is essential to ensure the effective participation of EVs in the transport and energy industry. In this way, every participant, from the EV user to the charging operator and to the electricity generation and distribution facilities, will not be adversely affected by the integration of the EV into the grid, but can also get the most benefit.

2. EV CHARGING SYSTEMS AND REQUIREMENTS

Although EVs may have different energy sources according to their type,the main energy storage units are the batteries. EVs can basically be classified as hybrid electric vehicles (HEVs) and all-electric vehicles (AEVs). AEVs are divided into battery electric vehicles (BEVs), which depend on the grid to charge the storage unit, and fuel cell electric vehicles (FCEVs), which do not require an external charging system. In addition, some of the HEVs, namely Plug-in hybrid electric vehicles (PHEVs), charge their batteries from the grid [50]. An EV charging infrastructure consists of the power infrastructure, the control system, and the communication infrastructure [51].Electric vehicle charging is divided into various classes as shown in Figure 2.1.

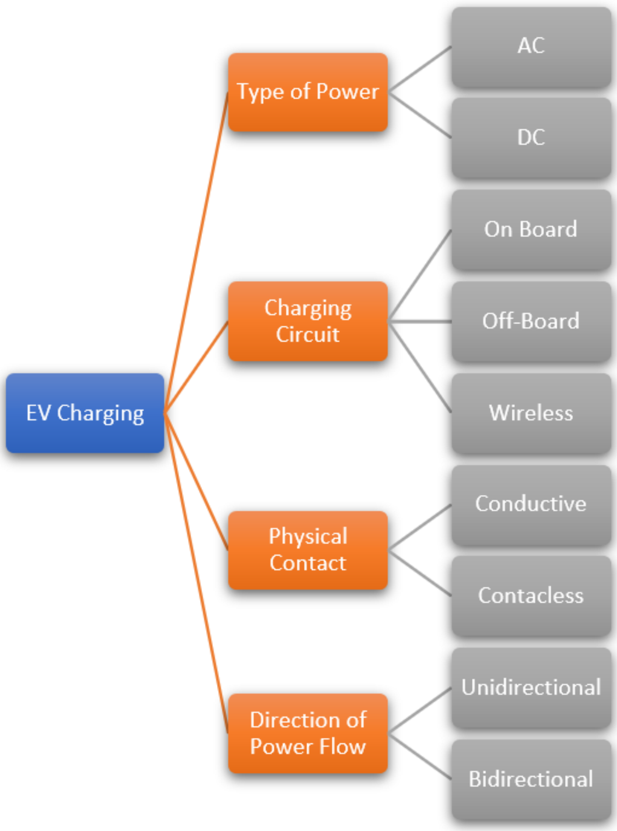

Figure 2.1 : Types of EV Charging [20].

Electric vehicle charging can be divided into AC and DC charging according to the type of power used, and level 1 (110-120 V AC), level 2 (220-240V AC) and level 3 (200-800V DC) according to the charging voltage levels [20]. Secondly, EV charging can be classified as on-board and off-board based on the location of the charger. An on-board charger is located inside the EV, it has the advantages of being compact and cost-effective and can be used for charging the vehicle almost anywhere where power source exists. However on-board charger allows the vehicle to be charged at a lower power, so the vehicle charges much more slowly. Off-board chargers, on the other hand, have different options as slow and fast charging, but the installation costs of these chargers can be quite high. In addition to on-board and off-board chargers, wireless charging is another type of charging that is carried out with the coil installed outside the vehicle and the converter placed inside the vehicle [52,53].

When EV charging is evaluated in terms of physical contact, it can be classified as conductive charging with physical contact between the power source and the storage unit in the vehicle, and contactless (wireless) charging without physical contact [54]. Efficiency reaches over 85% in wireless charging provided with separate technologies such as inductive coupling, capacitive coupling, resonant inductive coupling, permanent magnet coupling [55]. The charging levels mentioned above as Level 1, Level 2 and Level 3 applies to both conductive and wireless charging cases. In table 2.1, EV charging speed on level 1,level 2 and level 3 are compared.

Table 2.1 : EV Charging Speed on Level 1, 2, 3 Chargers.

	Level 1 Charging	Level 2 Charging	Level 3 Charging (DC Fast Charging)
Voltage	110-120 V AC	220-240 V AC	200-800 V DC
Max Power	1.44 kW - 1.9 kW	3.1 kW- 19.2 kW	Up to 350 kW
Typical Charging Time	8–10 hour. 3–8 km of range per hour of charging	4–8 hour. 16–32 km of range per hour of charging	30–60 minutes. 100–130 km of range per hour of charging
Charging Circuit	On-board	On-board	Off-board
Location	Residental	Residental	Commercial
Connector	SAE J1772	SAE J1772	CHAdeMO/ CCS COMBO 2

EV chargers are further divided into unidirectional and bidirectional topologies depending on the direction of electrical power flow. Unidirectional chargers with a less complex structure use a unidirectional rectifier and a DC-DC converter, while a bidirectional charger has a bidirectional DC-DC converter in addition to the rectifier. Unidirectional charging causes fewer connectivity issues compared to bidirectional charging, but it cannot serve the grid as the battery discharges as bidirectional charging does. On the other hand, the disadvantage of bidirectional charging is that it may affect the battery life due to discharge [20].

2.1 Smart EV Charging

As the demand for electricity is increasing with the rising trend of EVs, new approaches are needed to meet the electrical power demand optimally and to ensure the sustainability of this market. This may cause voltage fluctuations in the electricity grid, especially as it is obvious that many EVs will need to be charged at the same time due to the daily routines of citizens and in an uncontrolled manner. Qian et al. have revealed that a 20% EV penetration causes a 35% increase in daily peak load for the worst case for various uncontrolled charging applications [56]. Besides, the impact of EV charging on the grid depends on many parameters, such as the state of charge (SOC) and capacity of the EV battery, the charging mode and the load profile of the available feeders, and these parameters are often uncertain. This is a factor that complicates the operation of the distribution grid in case of high-density EV penetration [4].

In order to optimize the EV charging, to eliminate its disadvantages and even to turn them into advantages, it is necessary to make regulations on various issues. There are several studies to ensure more efficient use of the electricity grid and to reduce the costs of charging infrastructure for increasing EVs. Although these studies are divided into many subtitles, uncertainty modeling approaches and smart charging control approaches stand out.

The uncertainties in EV charging are mainly due to the uncertainty of the EV charging demand and the uncertainty of the electrical load in the system. In particular, the uncertainty of the charging demand arises from the parameters such as battery capacity, SOC, arrival and departure time at the charging station, resulting from the EV itself or user behavior. In addition, EV charging can become quite complex when operational parameters such as the service time of the charging station, the total number of instant users and the overall charging demand are considered [57]. The most common studies to overcome the uncertainty of charging demand are Monte Carlo [58] and probability distribution [59] based modeling methods. In addition to these, hybrid models [60] are also being developed to increase accuracy and minimize computational costs.

The increase in EV charging demand brings with increase in load capacity as well as uncertainty. It is clear that simply plug-and-charge without any coordination is not sustainable for the grid [20]. Optimum fulfillment of EV charging demand is directly dependent on the availability of grid service. In short, EV charging cannot be considered independent from the influence of user charging behavior and infrastructure services.

The solution to avoiding the mismatch between electricity supply and demand is the flexibility of both EV drivers and grid operators. This introduces the concept of smart charging. In the most basic sense, smart charging is to perform the charge in an optimum way by controlling the charging speed and duration. The smart charging also a concept that was born to benefit from renewable energy efficiently and to contribute to the grid [61]. With smart charging, besides avoiding the overload on the grid, charging costs can also be reduced and the profits of both the EV user and the grid operator can be increased. However, there are barriers to smart charging, such as vehicle owners' fear of not having control over the vehicle's charging. According to study of Brey et al. in Netherlands, EV drivers are willing to implement smart charging but want to have control [62]. Smart or coordinated charging can be accomplished by charging EVs during a time period when the load demand from grid is at the least, but this is not always the most comfortable solution for EV users. For this, many charging algorithms are being developed that can both overcome the fear of vehicle owners not to charge and make the system more feasible.

EV smart charging algorithms can be classified according to the target time intervals that they offer solutions as medium-term (weekly or monthly) operational optimization, day-ahead (daily) optimization, intraday (hourly) optimization and real-time optimization [63]. Smart charging algorithms can be optimized based on different purposes, such as the profit of the grid operator or the satisfaction of the EV user. In the study in [64], a comparative analysis was made with three different approaches. The first of these approaches is customer-based, the second is grid operator-based, and the third is based on the coordination of both the customer and the grid operator. In this comparison, which is handled in terms of peak load, load factor and total charging costs, it is seen that the third approach, which aims to reach the common goal based on the coordination of the EV user and the grid operator, offers the most optimal solution.

There are various studies on smart charging algorithms developed by targeting possible problems in the grid (voltage fluctuations, power losses, aging of grid equipment due to overload, harmonics). In [65], three charging algorithms were developed to reduce the effect of the load caused by EV charging on the grid, and it was observed that the computational speed of the algorithms whose objective function was load variance and load factor is better than the algorithm whose objective function is to reduce power loss. In [66], an approach that aims to provide voltage stability with heuristic optimization method is suggested. This smart charging algorithm calculates the load flow and checks the working conditions of the grid, the load status of the power system and the voltage change. If it detects any problems, it cuts off the charge of the EVs and puts them on hold. In [67], the authors present an EV charging strategy using horizon optimization technique that aims to both reduce the customer cost and improve the load factor by spreading or shifting the peak load time intervals, i.e. valey filling. In this study, without considering the uncertainty about the driving model of EVs, a price analysis is made with this combination to find the optimized solution. In [68], on the contrary, an smart charging approach, which can reduce the energy cost up to 9% for both ramp and steady state, and optimizes production costs with a meta-heuristic technique compared to valey filling method, is proposed. Main classification of EV charging optimization strategies is shown in Figure 2.2.

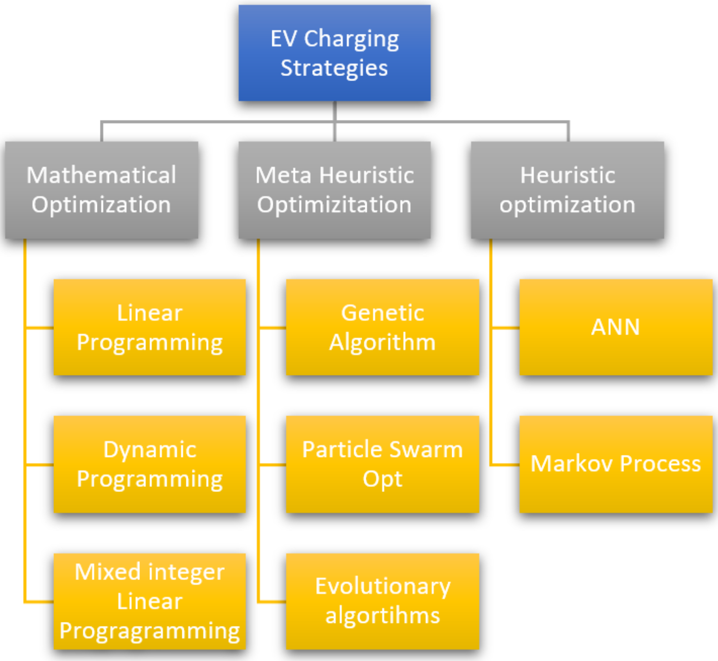

Figure 2.2 : EV Charging Strategies.

3. EV-GRID INTEGRATION (EVGI)

3.1 Challenges of EVGI

As mentioned in the previous sections, uncontrolled EV charging is bound to have serious impacts on the grid. The possible disruptive effects of this situation on the electrical grid are also an issue that is examined in the literature. The main problems addressed are as follows.

3.1.1 Voltage drop, instability and inbalance

Intensive integration of EVs into the grid and uncontrolled charging may cause overload, increase in line losses and a short-term voltage drop [69]. It causes voltage instability due to high demand from EVs to be charged, which can result in power outages in the distribution system. Other devices connected to the grid may also be affected and harmed by voltage instability. In the study in [70], a voltage deviation of 10% was analyzed at 30% EV penetration. In addition, in three-phase systems, unbalanced load distribution in lines can cause unbalance in phase angles and power quality may decrease due to voltage imbalance in phases [71]. With control methods, these problems can be solved and greater EV penetration can be achieved.

3.1.2 Overload

As a result of electric vehicle grid integration, the load demand to be produced and transmitted increases. Writers showed in the simulation in [56] that 20% EV integration can result in up to a 35.8% increase in daily load demand. Since local distribution elements, transformer equipment and supply cables are not designed to handle these extra loads, they experience very high levels of stress and can be damaged [71]. Over-current and low voltage in the system due to uncontrolled charging, increase the load on the transmission lines. This can have a serious effect on the load curve of the power grid. As a result, it is inevitable for the system to become more prone to malfunctions [72].

3.1.3 Power losses

Grid integration and high demand of electric vehicles at similar time intervals may cause significant power loss due to the non-linearity of their loads [73]. In study [74], it is shown that power losses reaching 40% in case of integration of 60% of EVs into the grid. This could seriously affect the stability of the power network.

3.1.4 Frequency change

In the model analyzed in the reference [75], it is observed that peak demand increases up to 31% in case of integration of 50% of EVs in the Danish distribution grid. If there is a serious imbalance between generation and demand, variations in frequency may be observed. The frequency of the power system should always be kept within a certain range, otherwise damage to the electrical system may occur [76]. This problem should also not be ignored, as uncontrolled charging of EVs may result in a load increase resulting in a frequency change [77].

3.1.5 Harmonics

Since EV chargers are devices that require power conversion, they generate harmonics, which can lead to harmonic pollution when EV penetration is high [78]. Due to harmonics, power quality may decrease and equipment may be damaged [79]. Although some studies say that the total harmonic distortion (THD) due to EV charging is less than 1% most of the time [74,80], there are also studies showing that it can increase up to 45% [81].

In addition to all these disadvantages and challenges mentioned, the literature also focuses on is minimizing the effects on the distribution network and even making it beneficial for the distribution system. Despite all these negative effects that EV charging can cause, it is possible to increase the efficiency and power quality of the grid if proper grid and EV interaction is ensured, the smart charging applications mentioned in the previous section are developed and the energy management strategies mentioned in Chapter 4 are implemented. By providing effective power management, peak load demand can be optimized. Thanks to controlled and appropriate charging methods, voltage imbalance can be eliminated and frequency regulation can be achieved. Uncertainties caused by renewable energy sources can be eliminated by storing energy and it can be advantageous in terms of cost [20]. In Figure 3.1, some challenges and opportunities of EVGI are shown.

There are promising studies that turn EV grid integration into an advantage by improving the load profile or increasing the load factor [82,83]. In fact, It can happen when vehicles discharge their energy to the grid. As a result, the concept of vehicle-grid integration has become not only a grid to vehicle (charging mode) but also a concept from vehicle to grid (discharging mode) [84]. This creates an approach in which both charge and discharge must be effectively controlled.

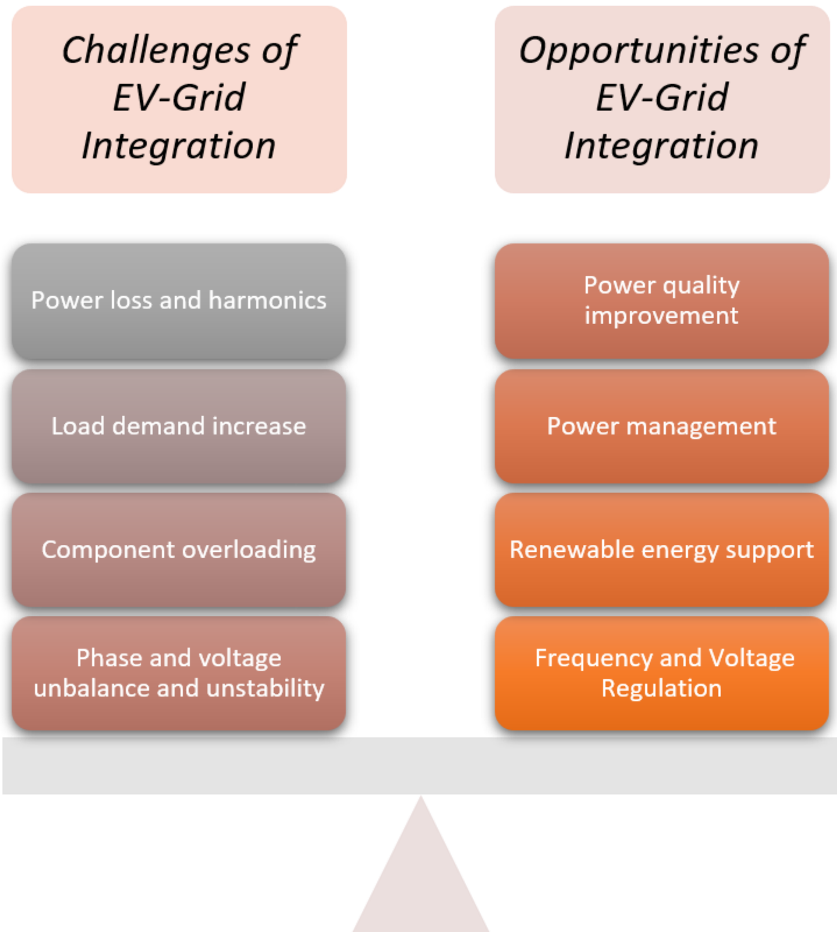

Figure 3.1 : Challenges and Opportunities of EVGI.

3.2 Vehicle-to-Everything (V2X)

Considering that EVs spend about 60% of their time parked at charging stations without being charged [15], they can offer a solution in terms of both reducing the cost and power demand during peak hours by making the best use of the idle energy of EVs during this period. In Figure 3.2, the time that EV spend during the day is shown [85]. Establishing infrastructures that support vehicle and grid integration can result in significant increases in the quality of the electrical grid. The methods in the literature generally aim at voltage regulation, peak power shaving, load balancing and reduction of interruptions as mentioned in the previous section, and the results are promising [19]. The controlled use of battery reserves in various applications while EVs are at the charging station and connected to the grid reveals the concept of vehicle-to-everything (V2X).

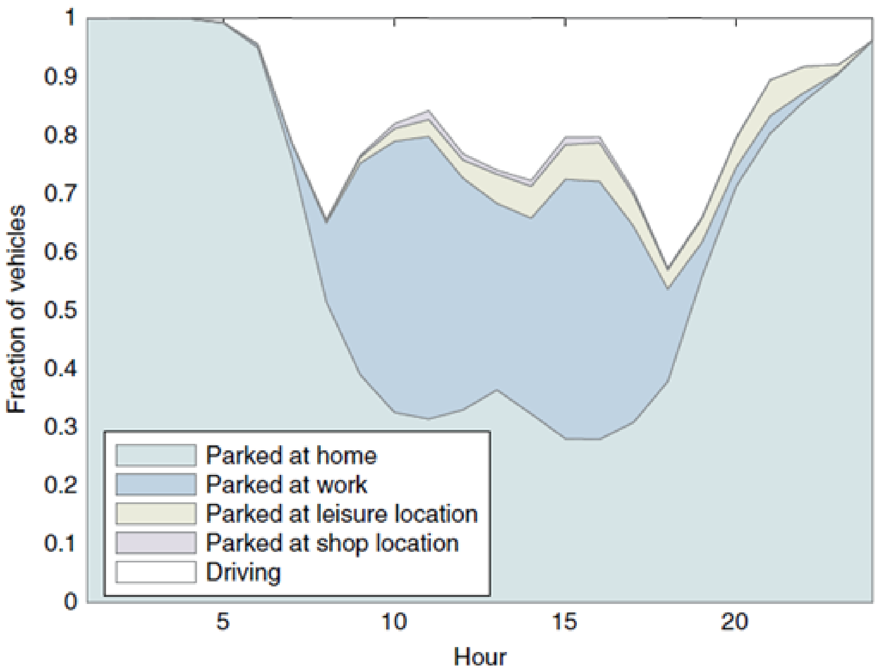

Figure 3.2 : Daily Usage of EV [85].

V2X applications provide energy flow for purposes other than operating the electric vehicle. A vehicle with V2X feature can transfer the electrical energy from the battery to an external application. In these applications, the unit to which the energy is transferred can be a smart home or building. Moreover, the vehicle can also supply electricity directly to the grid. Vehicles compatible with bidirectional electricity flow to the grid are called gridable electric vehicles (GEVs) [4].

With this concept, where EVs can act as a power source and provide a variety of services through energy exchange to the grid, the benefits may vary depending on the type of service and market regulations. With the flexibility of EVs, concepts such as vehicle-to-grid (V2G), vehicle-to-building (V2B), vehicle-to-home (V2H), vehicle-to-vehicle (V2V) have emerged. These definitions are related to the unit in which electrical energy is transferred. These concepts also differ according to the scales of the application. The Figure 3.3 shows various V2X implementations [61].

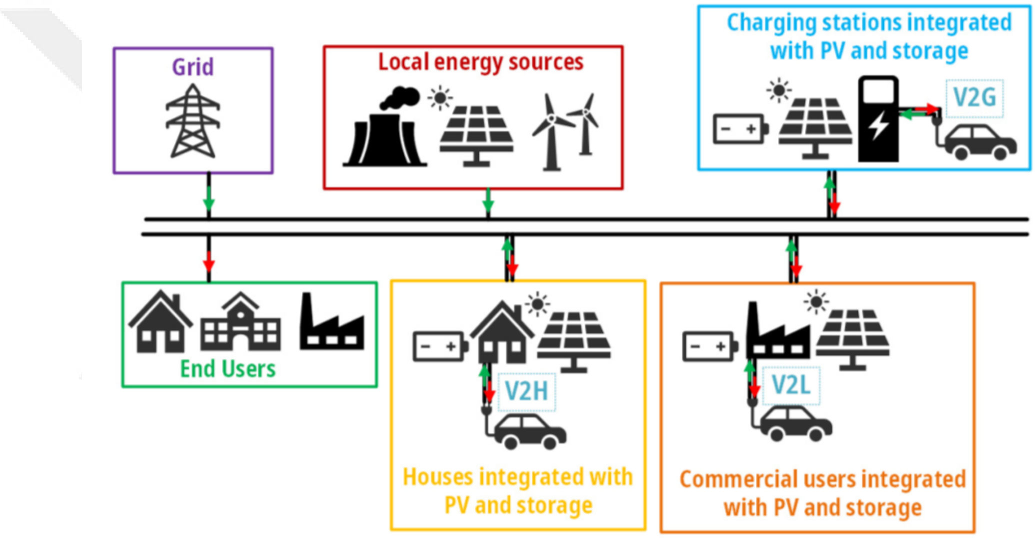

Figure 3.3 : Vehicle-to-everything (V2X) [61].

V2X services, that EVs can perform might need a fleet of vehicles of different scales. This can range from a small-scale V2H application where a single vehicle is used to power a home's critical systems, to a community where there may be tens of thousands of vehicles providing large-scale services. For example, V2H is generally with 1-3 number of EV and is designed for home back-up supply. V2B, on the other hand, is an application made with a number of 1 to 30 EV, aiming to help the building's back-up supply, as well as the power correction factor, to help the electricity quality. V2G application, on the other hand, is a larger-scale application that aims to provide effects such as voltage and frequency regulation to the grid with more than 50 vehicles [18,86].

In EV fleet charging or the applications that PV and EV are used together, cooperation is made thanks to EV aggregators that provide charge coordination. The EV aggregator can be thought of as a charge station manager that coordinares the charging of the EV fleet.

3.2.1 Vehicle-to-home (V2H)

The most convenient and comfortable charging for EV users is to charge in the parking lot at home. V2H is the service in which the EV is charged overnight in the parking lot of the house and partially or completely meets the energy demand of the house. Even the concept of smart home is structured together to provide the energy needs of the house with the concept of V2H. This concept often includes optimal energy management, energy production with solar panels for achieving the maximum benefit from V2H and smart home. Vehicle-to-home can generally be seen as an easy V2X application, as it does not require direct coordination between vehicle fleet and network management as in V2G [18,86]. However, V2H may require separate subpanels that transfer power to critical loads in the home. Also, since home appliances use AC power, there is a need to convert the DC power in EV's battery. Vehicle-to-home is mainly used for backup power until utility power is restored in the event of a power outage, or in combination with PV integrated into the smart home system as seen in Figure 3.3. In this way, EV and all electrical appliances in the house are controlled together with the smart home energy management system. V2H can reduce peak load demand, improve load demand profile, and even result in zero power supply from the grid [18,86]. In this context, Haines et al. have implemented a V2H application to smooth out household load peaks [87].

V2H can help reduce the negative effects of renewable energy sources (RES) and increase the reliability of power supply. With the V2H mode, the efficiency of the grid can be increased by minimizing energy losses and increasing operational flexibility in the smart home energy management system [86]. It is also important to improve charge/discharge strategies for EV to participate in these services in the best way possible. The most well-known example of this is the V2H service that Nissan provides with Leaf EVs to provide backup power for grid security in the areas around the

Fukuhara nuclear power plant failure in Japan [88]. V2H can be used to meet the part load demand of a house for economic benefit. It can help reduce the electricity bills of the house by charging the vehicle when the electricity price is low and discharging it when the electricity price is high. By providing efficiency in this way in many homes, it can contribute to the development of the entire grid [18,86,89]. In Figure 3.4, vehicle-to-home application and integration of PV are shown with an illustration [90].

Figure 3.4 : Vehicle-to-Home with PV Integration [90].

3.2.2 Vehicle-to-building (V2B)

V2B is the energy transfer mode of an EV battery to a commercial building (workplaces, schools, malls) to support internal loads, to reduce the mismatch between supply and demand, within the scope of energy management planning for the building. In this way, when EV users park their vehicles in the building, the peak load of the buildings can be reduced by load shifting [86]. Millner et al. have implemented V2B to reduce peak demand with E-trucks [91].

Flexible energy planning for buildings and EVs can be done with V2B. Vehicle-to-building service can provide energy transfer to buildings as an emergency in case of blackout. In Figure 3.5, emergency or daily use of V2B application can be seen [92]. Due to the narrow scale of V2B, there is less variation in V2B strategies. If the application is applied in larger diameters when it is not required for building, it may also be possible to use it for benefits such as frequency regulation for grid [86,89].

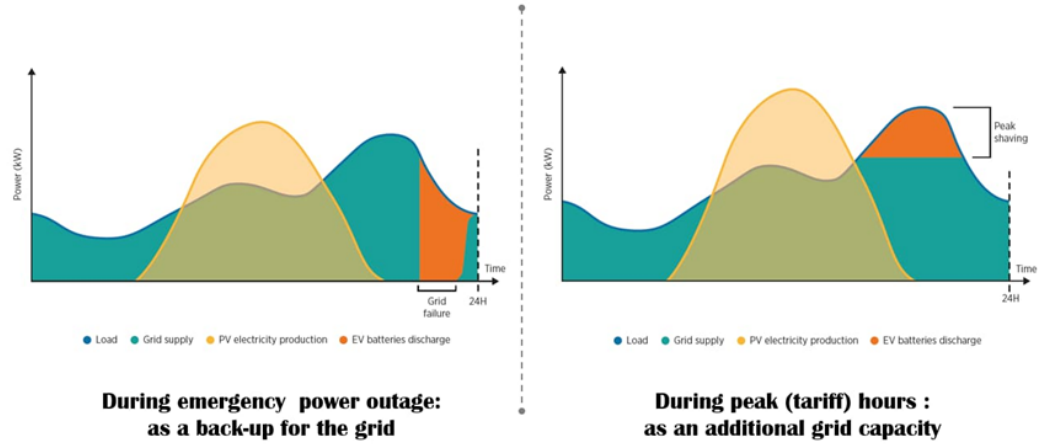

Figure 3.5 : V2B Services for Emergency Power Outage and for Daily Peaks [92].

3.2.3 Vehicle-to-grid (V2G)

V2G service is the integration of multiple EVs in parking lots, smart buildings, EV charging stations into the grid through the aggregator and providing various benefits to the grid assets and grid's energy planning. V2G, which was first proposed by Letendre and Kempon in 1997, is predicted to support the study of the discontinuous nature of renewable energy resources as well as being a energy storage units [93].

Electricity system operators, regional transmission organizations and distribution services can benefit from this service. EVs in charging stations are connected to the medium voltage grid with transformers and necessary distribution equipment, while EVs in buildings are connected to the low voltage grid [18,86]. The service scope of V2G is wider than V2H and V2B. In Amsterdam, there is a pilot implementation of the Mitsubishi Outlander PHEV fleet providing both frequency regulation and energy reserves [94]. In Figure 3.6, an example of V2G operation can be seen [95].

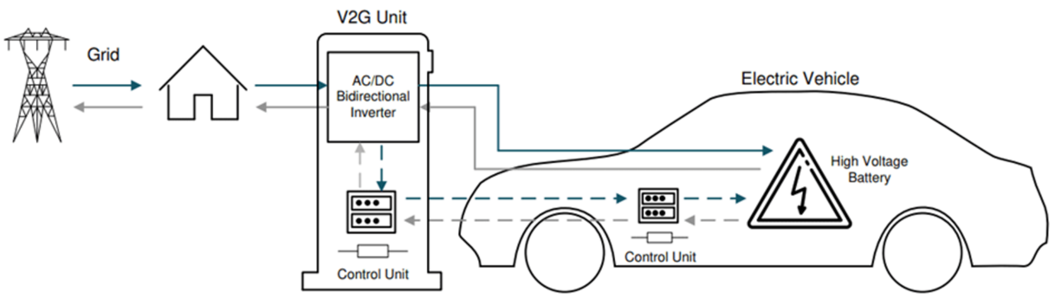

Figure 3.6 : Vehicle-to-grid [95].

Charging in which the power flow is unidirectional is sometimes referred to in the literature as V1G [18]. It is the application of cutting off the charge with the demand response mechanism, that is, reducing the charging rates or stopping the charging process upon demand from the grid. In the study by Kaluza et al., nearly 100 BMW i3 vehicles responded to a total of 209 requests during the 18-month test period, and charging was stopped or the charging rate was reduced [96].

A comparison of unidirectional and bidirectional services is given in the Table 3.1.

Table 3.1 : Comparison of uni- and bidirectional EV charging.

Features	Unidirectional	Bidirectional
Power Flow	Grid-to-vehicle (G2V)	Grid-to-vehicle (G2V) and Vehicle-to-grid (V2G)
Complexity	Low	High
Cost	Low	High
Infrastructure	Communication	Communication and Bidirectional Charger
Services	Load Profile Management, Frequency Regulation	Backup power support, Frequency and voltage regulation, Active Power Support
Disadvantages	Limited Service	Battery Degradation, Cost, Social Barriers

3.2.4 Vehicle-to-vehicle (V2V)

V2V is energy transfer between vehicles to meet the energy demand within a relatively small-scale community. EVs as flexible power providers and receivers transfer power between them. In a microgrid, EVs with a charge request can be charged by another EV. In this way, a local neutralization can be achieved and the stress on the grid is reduced. In V2V mode, consensus is usually achieved through negotiation between EVs rather than a centralized unit. Individual interests of the EVs and the load management of the total system are taken into account. In this application of interaction between two or more EVs, efficiency can be also differ depending on the location of the vehicles or the amount of energy shared [97]. In Figure 3.7, an example of V2V operation in a distribution grid is shown.

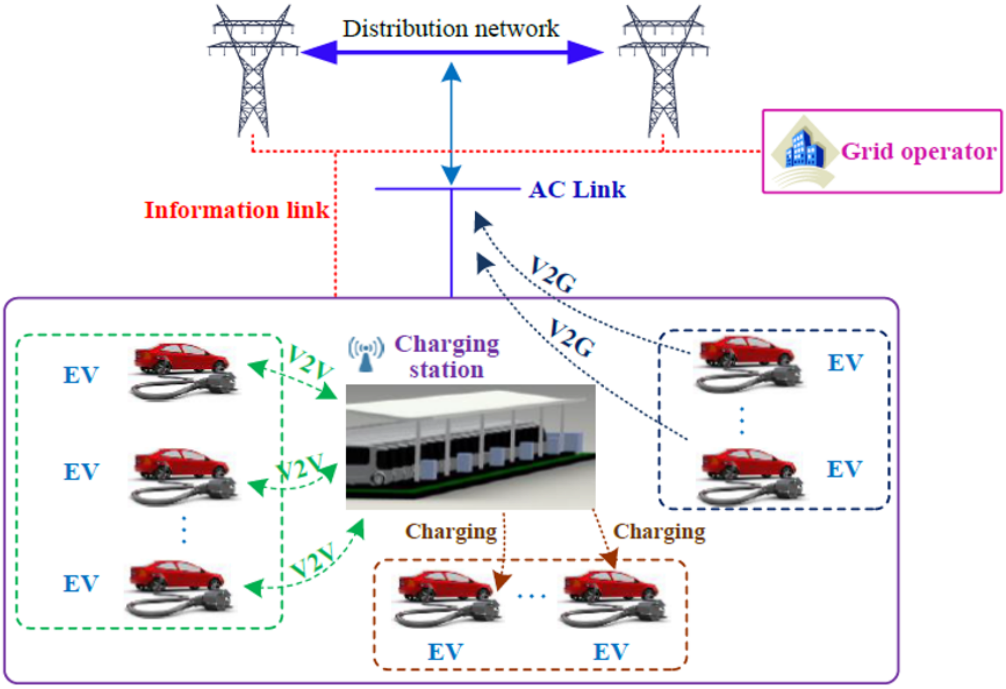

Figure 3.7 : Vehicle-to-vehicle operation in the distribution network [88].

3.3 Benefits of V2X Operation

In this subsection, the potential benefits of V2G, which are the most comprehensive of V2X applications, are discussed. In fact, V2G can be thought of as a system that works as a distributed energy source with the intelligent communication and control system between EVs, the aggregator and the system operator. With the V2G service, EVs can provide services such as frequency/voltage support, load balancing, support of solar/wind power, load balancing, valley filling and peak shaving as shown in Figure 3.8. It should be noted that the potential of V2G depends on the EV owner's driving behavior and overall infrastructure. There are studies evaluating the efficiency of V2G depending on these parameters [19].

Figure 3.8 : V2G Services.

3.3.1 Frequency and voltage regulation

In the V2G application, the highest priority is given to the voltage and frequency regulation of the grid. The balance of supply and loads can create a tendency to deviate in the frequency of the system. This is more likely to happen, especially in microgrids where production and consumption are more variable [98]. Today, frequency regulation is carried out with generators working with expensive fuels. Thanks to V2G, frequency regulation, one of the most important issues regarding grid stability, can be achieved by managing the charge/discharge of grid-integrated EVs. The charge and discharge of the EV battery can be regulated quickly by adjusting. It is also possible to provide active and reactive power support with V2G [18].

With the V2G application, a frequency feedback regulates the EV power output to respond to frequency changes while ensuring that the EV does not go below the requested SoC level. In this way, the deviation in frequency can be regulated [19]. Mu et al. analyzed the efficiency of EVs in grid integration and frequency regulation service [99]. The results showed that EVs will provide significant assistance in frequency regulation to increase grid stability. Khalid et al. To examine the effect of EVs on voltage stability with V2G service, he conducted a study showing that it can improve grid stability [100].

3.3.2 Peak shaving and load balancing

The stress on the grid also increases as electricity demand increases. It can result in power outages in the worst case scenario. As the demand increases, V2G service can be used to balance or shave it. V2G mode helps with peak shaving by discharging the EV battery during peak demand times of the grid and can flatten the load curve with valley filling during off-peak times. This benefits economic, environmental and grid security. Peak shaving techniques provide a sustainable load profile and improve power quality. Load balancing refers to a short-term reduction and subsequently an increase in load when demand decreases, while peak trimming aims to reduce the peak load. Change of the load profiles by load levelling and peak shaving can be seen in Figure 3.9. Of course, the size of the EV fleet and the efficiency of the algorithms are important in the performance of this operation [19,98].

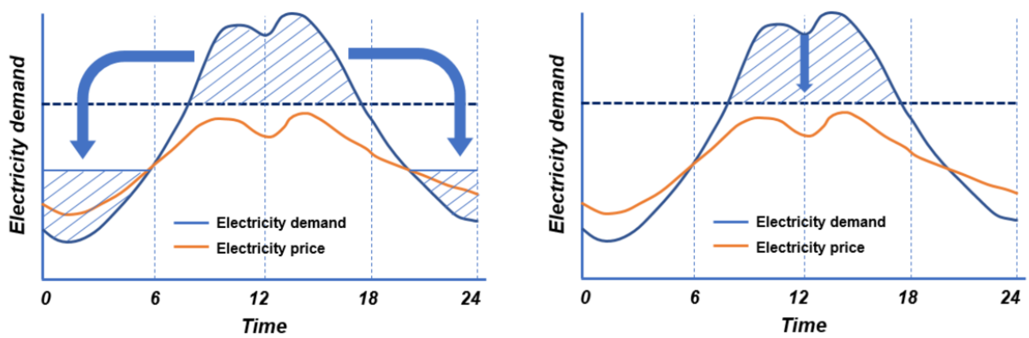

Figure 3.9 : Load leveling and Peak Shaving [19].

3.3.3 Renewable energy support

The integration of EV and RES is important to increase the use of RES and to ensure that EVs are completely green. Although increasing renewable energy sources are critical in reducing harmful gas emissions, they can have undesirable effects on grid quality due to uneven generation outputs. The output power of RESs are intermittent and unstable and difficult to control and integrate into electricity grids. The fluctuating output of the RES creates difficulties for the grid operator. EVs can be a quite important supporter in balancing power differences and ensuring stable operation. In a large-scale V2G application, EV battery storage provides flexibility to renewable energy and reduces power imbalances. EVs can transfer energy to the grid during low generation of the RES and recharge during high generation periods of the RES. In this way, the energy can be stored in a very efficient way. This ensures better grid stability and frequency voltage regulation and increases reliability in the path to developing renewable energy [18,19].

It is predicted that 5 million PEVs can reduce the annual renewable energy cut by 40% with smart charging [101]. Lund et al modeled the energy system in Denmark. In the study, they found a 20-30% reduction in wind electricity generation managed by a fleet of V2G-capable EVs [102]. Dallinger et al. combined a vehicle travel model, charging algorithm, and distribution grid model for EVs to evaluate its impact on renewable energy. They noted that EVs contribute to the change in net load and support the integration of RES [103]. Similarly, Nguyen et al. observed a four times reduction in power imbalances when integrating 600 EVs with wind energy [104].

3.3.4 Transmission and distribution upgrade deferral

Electricity facilities are obliged to provide the desired amount of electricity supply at the desired time and at the most affordable price. In order to meet the increasing loads, public institutions plan to ensure continuity of supply. A longer-term part of these plans is the upgrade of generation, transmission and distribution equipment, which requires costly capital. Deferral of these costly expenses considerably means huge savings for the organizations. The availability of flexible resources such as EVs can postpone such costly projects [18]. Dang et al. examined the potential of V2G and renewable energy sources for infrastructure upgrade deferral at the county level. They treated the problems that caused the need for upgrade, frequency and voltage related issues. As a result of the study, they found that if there is a V2G-capable EV fleet in the region, the transformer overload is reduced by 70% and the electricity cost is reduced by 17% [105].

3.3.5 Spinning reserve

In case of an unplanned events such as a loss of generation, the extra generation available to meet the demand is called the spinning reserve. In other words, it is not a service sent as a standard, but a service provided only in case of need. However, the spinning reserve provider is not only paid in service, but constantly paid because they have the capacity in the hands. If enough number of V2G compatible EVs are available, EVs can also serve as spinning reserve [19].

3.3.6 Environmental benefits

Since EVs operate with electrical energy, unlike ICE vehicles, the threat of harmful gas emissions from transportation can be avoided. Thanks to V2G, it is predicted that potential environmental problems can be significantly reduced and carbon emissions can be significantly reduced. However, it should not be forgotten that the source from which electric vehicles receive electrical energy is production centers with high emissions. In this context, the use of more RES is essential [106].

Zhao et al. studied the environmental impacts of using V2G-enabled electric trucks in five independent system operator regions. The lifetime of an electric truck that provides V2G service to the grid for 15 years has shown that it can prevent 200 to 500 tCO_2 emissions [107]. Hoehne and Chester conducted a study showing that V2G-enabled EVs reduce carbon emissions by 59% by balancing the supply and demand of the grid. In this study conducted for different scenarios, it has been shown that the result varies according to the charging time of the vehicles and even in some scenarios, V2G increases carbon emissions. This situation is directly related to the electricity generation profile in the region. Based on this result, the authors said that RES should be included in V2G applications [108]. Sioshansi and Denholm investigated the environmental impact of V2G implementation of spinning reserve services. Within the scope of the study, they examined CO_2, SO_2 and NO_x emissions.

As the output of the study, they showed that replacing 1% of an EV fleet with V2G powered EVs reduced emissions from electricity generation by 25% [109].

3.3.7 The other services of V2X

With the V2G service, demand side management can also be provided. Demand-side management includes the user's or customer's responsiveness to signals and flexibility in response to electricity demand. Demand-side management can be more effective in V2G mode when EVs are joined at peak time [98]. Keyhani and Ramachandran stated that when 50% of EV users are in V2G mode during peak hours, there is a 10.2% reduction in peak load without disturbing the user [110].

EV owners will also benefit if necessary adjustments are made in the V2G mode of the vehicles. First of all, they can increase their profits if they do not operate in V2G mode under a certain SoC in order to meet the driving need of the vehicle, they are charged in the process of transferring energy to the grid, and they also take the cost of battery deterioration. Another benefit is V2G's energy arbitrage service. The process of buying electrical energy when it is cheaper and selling it when it is expensive is called energy arbitrage. Leaving aside energy losses and other operating costs, it may be possible to make money from this difference [98].

3.4 Challanges of V2X Operation

Alongside the mentioned benefits of V2X, the challenges are also a topic to be discussed. Main problems such as network security, EV battery degradation, social barriers, economic difficulties are obstacles to the development of the V2X application. In addition, the unpredictability of electric vehicle user behavior affects the reliability of the service to be provided to the end user.Another issue is the environmental impact from EVs and V2X. Although EVs have positive effects on the environment, as the transition to electric power increases, the need for water for cooling in power plants is also increasing [111]. There are many different barriers for V2X as can be seen in Figure 3.10, the most emphasized areas in the literature are elaborated in the following section.

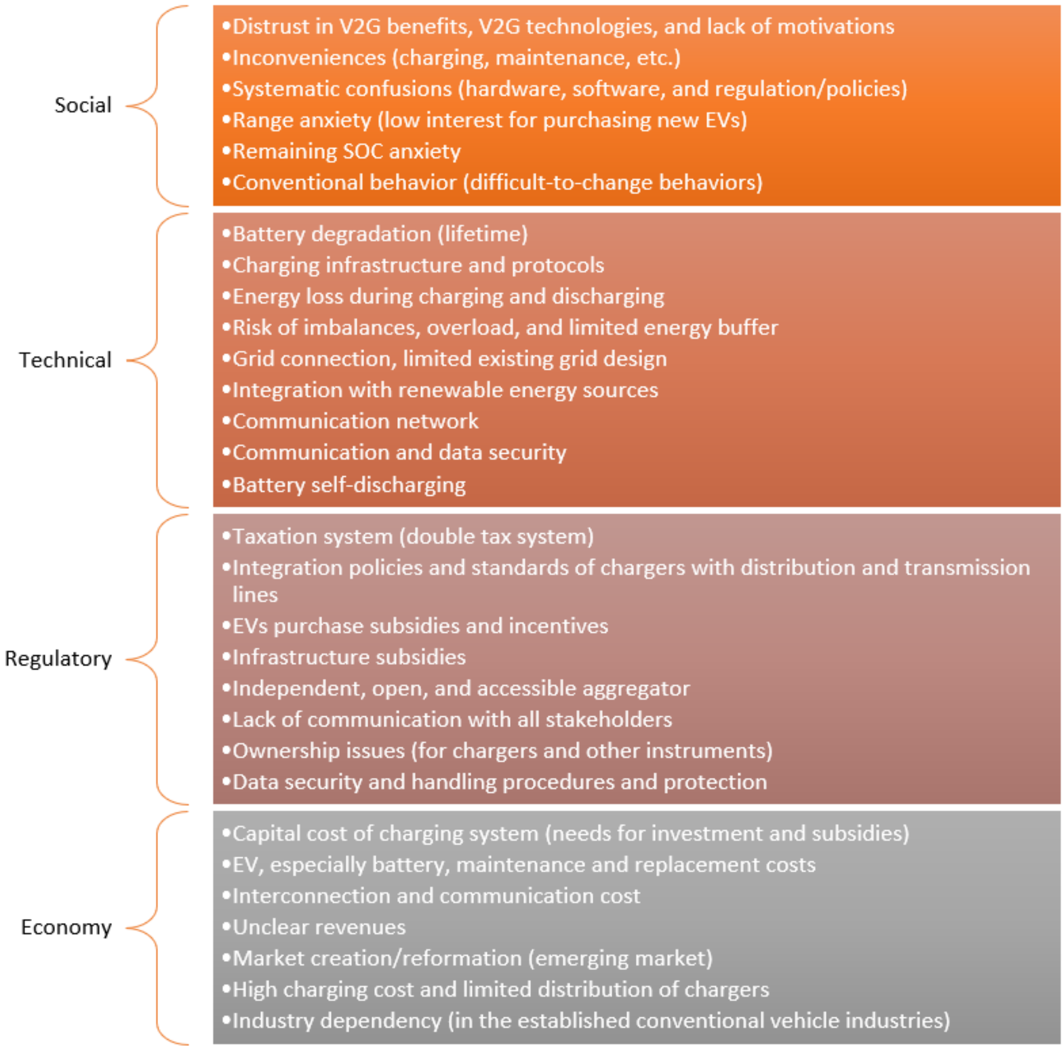

Figure 3.10 : Challanges of V2X [19].

As a result of a survey conducted in 2021 [61], it was concluded that the society is aware of the concept of V2G and that EV (PHEV, BEV) owners are interested in V2G. However, most of the EV owners stated that they would prefer to use it for their own household needs when necessary (possible blackouts, etc.). The most important common concerns stated by the survey participants were range anxienty and data privacy issues. It is important to invite EV users who are likely to be concerned about the implementation to collaborate with V2X technologies.

One issue that limits the applicability of V2G is that the grid does not have the same entitlement as EVs access. This will affect the flexibility of V2G as the grid will not be able to fully utilize the power in EV fleets. Since the primary purpose of grid-EV interaction is to charge EVs, it would be completely inappropriate to completely drain the EVs' power. In this case, only EVs above a certain SOC level will take part in V2G mode. This reduces the functionality of EV fleets [13]. The other problem is the cyber security issue brought by digitalization, which is indispensable for the sustainability of V2X. The size of the data, correct processing and transmission, and uninterrupted transmission between the network and the vehicle are challanging processes [18,19].

3.4.1 Battery degradation

Considering that a significant part of the cost of an EV results from the battery, the reduction of the battery's lifetime is an important evaluation criterion for the user. Battery degredation is mainly comes from calendar aging due to temperature and SOC, and cycle aging due to charge/discharge depth. As a requirement of V2X, the EV battery has to be charged and discharged repeatedly throughout the day. For this reason, it is argued that V2X will also have an impact on the life cycle of batteries. This may affect the social acceptance of V2X applications [19,106]. Considering that a Li-ion EV battery has an average of 500-3000 charge/discharge cycles, and this number can be affected by parameters such as temperature, charge power, charge depth, it seems possible [106]. The recommendation to avoid deep charging and discharging of the battery and using a small portion of the battery capacity is not a good solution as it will create many more charge and discharge cycles.

In a rather extreme case, Ribberink et al. have shown that daily repetition of V2G service, which transfers the entire EV battery's energy capacity to the grid at maximum power rates, will reduce battery life from approximately 9.5 years to approximately 5 years [112]. Bishop et al. examined the effects of V2G on EV batteries without cost analysis for different battery capacities [113]. According to the study, in case of implementation of V2G service, even in the best conditions, the vehicle is obliged to replace more than one battery during its lifetime.

Since studies of battery degradation have been simulated for V2X applications with very different load profiles and have also been examined for different battery chemistries, it is not surprising that the results are also very different. Uddin et al.

conducted a battery aging study on NCA type Li-ion batteries and showed that it is possible to extend the battery life even more in V2G state compared to normal charging, with proper modeling by keeping the battery capacity between 29-78%. They developed a battery aging model with the data obtained from degradation experiments, proposed a new strategy, and argued that using V2G with their proposed strategy could reduce the capacity reduction in Li-ion batteries by 9.1% [114].

3.4.2 Effects on distribution equipment

As EVs are connected to the grid with type 2 and type 3 chargers for charging, high power demand can be put on the distribution transformer and other equipments. With controlled charging, this effect can also be reduced and safety can be achieved. Moghe et al. show that in the case of 50% EV penetration, uncontrolled EV charging reduces the life of distribution transformers by 200-300%, while with controlled charging it increases by 100-200% compared to uncontrolled [115].

3.4.3 Designing compatible charger for V2X

Since the charger is basically a rectifier that converts AC to DC, it requires an in-vehicle inverter for vehicle-to-grid charging [18]. A solution is to use a bidirectional charger to both charge and discharge the battery with the same hardware, as the inverter used for traction power (to start the AC motor) may not be able to provide enough power. In the study in [116], a bidirectional charger with a power level of 2 kW, which can operate with 92% efficiency in charge and discharge mode, was produced. Although the power level is low, this study shows the potential of the application. In addition, using it outside the vehicle is another solution. In this context, the DC charging standard ChaDeMo stands out with its bidirectional power flow projects [117].

4. ENERGY MANAGEMENT SYSTEM FOR EV CHARGING

Integration of EVs into the grid creates a large additional power demand that can cause grid components and equipment to overload. Especially considering the conjecture that EV owners come back home from work and charge their vehicles at similar hours, these problems are inevitable if there is an uncoordinated charging. Due to the increased EV charging demand, local distribution elements such as transformers and supply cables will be affected by high stress level. It is necessary to coordinate EV charging in order to eliminate these problems and to maintain the power supply without any problems [118]. It is possible with the energy management system for EV charging, both to ensure the safety and reliability of the distribution network and to meet the EV charging demand in the best way and to ensure user satisfaction.

Consumers and producers, transmission system operator (TSO), distribution system operator (DSO) participate in energy management. Primary sources and RES can be directly integrated into the transmission grid and provide services to the TSO. On the other hand, consumers and distributed energy sources are integrated into the DSO. Another element of EMS is aggregator. According to the smart grid report, the aggregator is a legal entity that provides the opportunity to benefit from their flexibility by encouraging end users to retail electricity. In line with the aggregator's goal of keeping supply and demand in balance, it is possible for consumers to become prosumers, and thus DERs and PEVs become active participants of the network. The PEV aggregator, on the other hand, can be seen as a tool that enables both V2G and G2V mode to improve the performance of the local grid and to serve PEV users who hope to fast charge and minimize charging costs by taking into account system constraints. In the EMS algorithm, all these participants have separate functions and they all communicate to pass the necessary information to each other. The fact that information flows are generally bidirectional gives the right to active participation in PEV users, aggregators and DERs. Sharing and analysis of information is accomplished through communication protocols and IT [23]. In Figure 4.1, participants of EMS is shown.

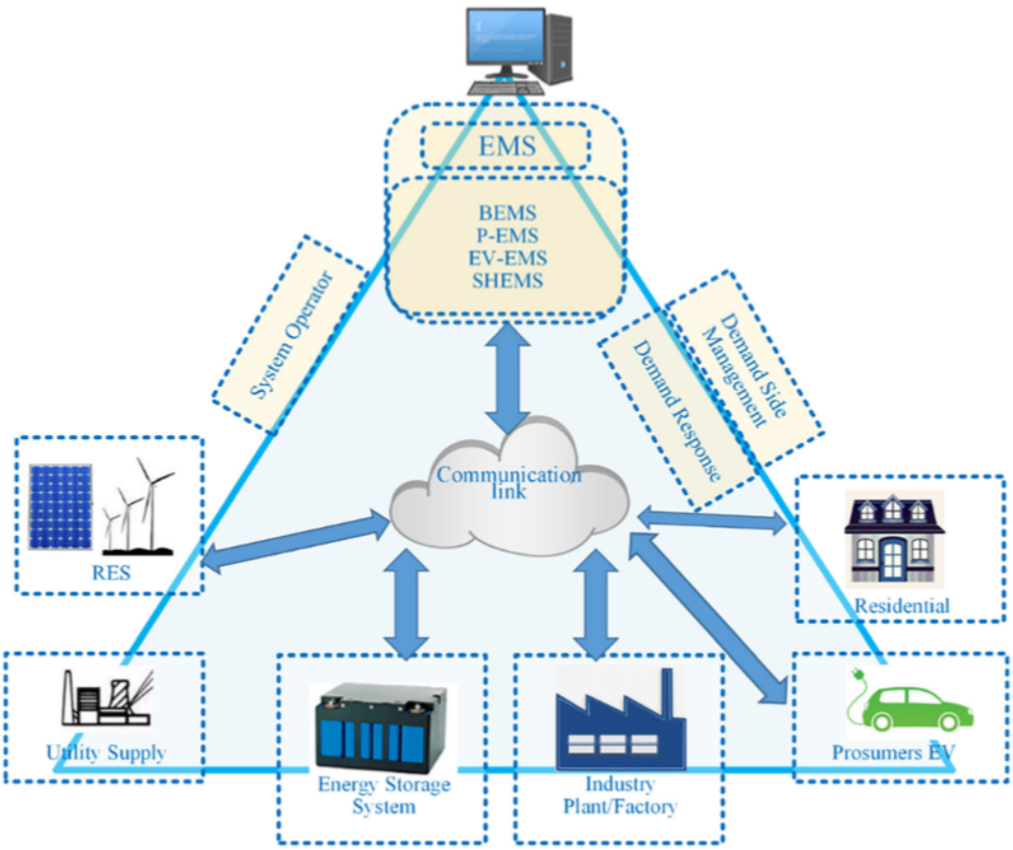

Figure 4.1 : Participants of EMS [23].

The main objectives of the EMS can be economic, environmental or technical. For example, EMS may aim to improve power quality or keep equipment performance at a high level, or it may aim to improve the lifespan of transformers. But when it comes to the energy management of PEV charging stations, the coordinated charging of the PEV, customers' expectations and cost should also be considered.

While determining the energy management approach for EV charging, objectives such as obtaining the optimum V2X operation, reducing the peak load and flattening the load profile is aimed. Based on these goals, charge coordination methods and charge algorithms are developed. Centralized and decentralized coordination methods come to the fore when controlling the power flow in EV charging stations. With these methods, the objectives of increasing the grid quality can be achieved, such as reducing power system losses, preventing transformer overload, minimizing voltage drop and improving the load factor [5,71,119].

4.1 Centralized Coordination

Centralized architecture is one of the EV charging coordination methods that basically a central unit organizes EV charging by processing information about all EVs in its area and obtaining the optimum solution, taking into account electricity company, grid quality and customer priorities effectively. Central unit or aggregator is responsible for the management of all EVs in its field and takes into account the demands of EV customers with the cost optimization it provides. While the aggregator makes regular demand forecasts with the inputs it receives, the DSO checks the load profile for grid security. In case of unusual or undesirable situations in the system, the aggregator is responsible for ensuring the safety and reliability of the system by taking appropriate measures [5].

Various studies in the literature [65,120,121] suggest central control methods to optimize EV charging and increase EV penetration. In this control method, basically, information from all EVs are collected centrally and optimization of charging profiles is centrally provided. The increase in the number of EVs is one of the biggest factors limiting central coordination. Under the central coordination architecture, there are sub- strategies such as online control and real-time charging.

4.2 Decentralized Coordination

In this coordination method, there is no dependency on any central control unit. In decentralized charging control, user satisfaction and electricity price are the most important factors that determine charging decision, EV user can directly chooses charging programs themselves. Although the choice of target SOC and charge time is given by the EV user, they can be manipulated by a unit such as a collector, with factors such as price signals [5]. On the other hand, focusing on user satisfaction and minimum cost plan can be a problem in the decentralized coordination architectures [30,122]. In most models, the assumption is made that the distribution grid infrastructure is strong enough to meet the demands of EVs at all times, but this assumption can cause problems especially in the evening or night when there is high charging demand [123]. However, in decentralized coordination, there are also quite effective methods that optimize grid requirements and EV demands, although the optimum solution for the overall system is not always guaranteed, as the demand of each EV takes priority. Decentralized architecture can also be divided depending on the communication network it has:

• Fully-dependent structure in which local controllers communicate via a central entity.

• Fully-independent structure where local controllers do not depend on any central entity for communication.

• Partially-independent structure where local controllers communicate both with each other and with the central entity.

In the first and third structures that communicate with the central unit, however, the decision is made by the local units, the central unit has no decision-making authority [23].

As a result, studies in the literature find the relatively new decentralized coordination more advantageous than centralized coordination because it is less computational complexity and user-oriented. These distributed coordination methods involve randomness in vehicle mobility and have lower communication requirements. Better known robust communication links such as SCADA, PLC or fiber optic are preferred in centralized EMS, while more cost-effective technologies such as WLAN, Zigbee, Bluetooth may be preferred in decentralized EMS [23].

4.3 Hierarchical Coordination

User data privacy, communication costs, and computation time must be considered when implementing EMS at the distribution level. Moreover, the comfort of the EV user should be a priority when determining the EMS for EV charging. While providing this, the security of the network should be taken into consideration and it should be aimed to increase the power quality. Hierarchical EMS is recommended as a hybrid approach by eliminating the disadvantages of both centralized and decentralized approaches and taking advantage of their strengths. The approach, which is neither centralized nor decentralized EMS, in which multiple microgrids are usually divided into two or three control level structures, is called hierarchical EMS architecture [39,120]. In this structure, there is a central controller and local controls that provide information to it. Thanks to the layered structure it provides, it can eliminate the excessive processing load of the central architecture, while it can be a solution to the disadvantages such as the decentralized structure not making global optimization. The handicap of this architecture is the interruption of information transfer in case of error at any level. Centralized, decentralized and hierarchical control schemes are shown in Figure 4.2 [124].

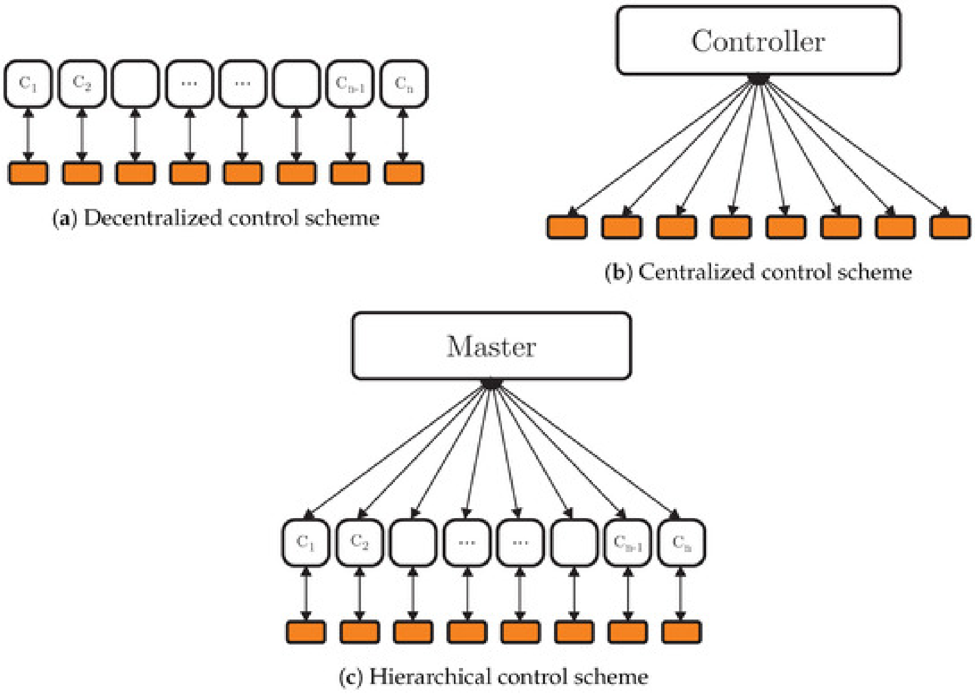

Figure 4.2 : Centralized, Decentralized and Hierarchical Control Schemes [124].

As a result, while centralized EMS is an application targeting global optimization, it is not very suitable for application to multiple microgrids due to communication cost and computational burden. On the other hand, decentralized architecture offers low computational overhead while remaining far from the global optimum. For this reason, hierarchical architecture is seen as the most suitable option for microgrids with different control levels [19,23]. In Table 4.1, the disadvantages and advantages of EMS architectures is compared.

Table 4.1 : Comparions of EMS Architectures.

	Advantages	Disadvantages
Centralized	Global optimization Overall operating cost reduction Easy implementation	Lack of costumer privacy Complex and expensive communication High computational burden Poor extendibility and flexibility
Decentralized	Higher Costumer privacy Distrubuted computational burden on EMS High Flexibility Higher consumer acceptance Higher fault tolerance	Higher total cost Lack of exact optimization Need of effective communication system
Hierachical	Higher flexibility and extendibility Layerwise control Higher reliability and security Suited for MMG High Accuracy Abilitiy to handling power quality and operating cost Scalable and adaptable for EV Fleets	Complicated control and implementation

In all of the EMS architectures mentioned, different optimization methods can be applied according to various objectives [23].

4.4 Agent-Based Approach

The agent-based approach is the modeling of the system at the local level, which is handled with the smallest units called agents. These models are used to examine the effect of agent behavior and interaction of agents on the system. When applying this approach, it is modeled with three main characteristics of the factors; obtaining information, making decisions and reacting as seen in Figure 4.3. Agents should be able to take information about the conditions in the environment, process this information and decide autonomously, and then give feedback to the environment as a result of this decision [125].

Figure 4.3 : Control Process of An Agent.

Agents represent active entities of the system that sense and manipulate its environment. Ferber defined an agent as a real or virtual entity that operates in an environment whose behavior is autonomous, can perceive and act, and interact with others [126]. Agents, inputs, and initial state are defined by rules of interaction with other agents and decision-making flow. An agent can interact with others in line with their individual or global goals and make their own decisions and provide various services to their environment.

Although all agents are modeled in the same way while modeling, the input and output parameters of the factors and the environmental conditions may be different. One of the features that facilitates system modeling is that the agents can be defined, modeled and then reproduced by copying. In addition, one of the biggest advantages of this approach is that the states of the agents can change dynamically even during simulation, the system can be constantly updated by removing existing agents or adding new agents. Therefore, agent-based approach is very suitable for long-term and variable scenarios [37,125]. Agent-based modeling is a type of software development approach that consists of many units that make their decisions locally. This modeling transforms the decision-making process into a computer-assisted approach. An advantage of this approach is that a fault in a single unit will not affect the rest of its system. This makes the system more resistant to potential failures.

In EV charging management, on the other hand, agent-based approach represents the coordination where chargers or EVs are called agents and the decision process is carried out independently from a centralized structure. In the this approach, the priority is usually to provide user satisfaction [5]. Each of the agents knows the data needed to manage EV charging and can negotiate with other agents. The agent can make a decision as a result of local information and negotiations. However, in this case, the process should be repeated continuously in terms of reliability, since each agent will make its own decision [36]. In addition, for the good of the general state of the system, hierarchical architectures, generally called multi-agents, can be used. Agent based modeling is also the general name of the approach used in the modeling of Multi-Agent Systems (MAS) in the literature. Although there are no different definitions for agent-based modeling and multi-agent system in the literature, MAS defines a system in which multiple agents interact with each other.

5. SWARMGRID-X IMPLEMENTATION TO CLUSTERED EV CHARGING SYSTEMS

Within the scope of this thesis, the MAS-based approach in the Swarmgrid-X algorithm, which is the extended version of the swarmgrid algorithm, is inspired. The proposed approach is integrated into clustered EV chargers. In the approach, it is aimed that each charging unit in a charger cluster negotiates with each other without a central unit, thereby achieving the goal of power neutralization within the cluster. This section discusses the details of the proposed approach.

5.1 Swarmgrid Approach

The Swarmgrid is a decentralized approach based on the MAS, where all elements in a distribution network are controlled by an agent. The multi-agent system here is a swarm. This approach provides a swarm control in line with the local targets of the agents, with its completely decentralized structure. Agents' behavior is determined by the agent based on local knowledge and the outcome of negotiations with other agents, resulting in action. Agents do not always have to communicate with every agent, and communication partners may change over time. However, each agent still has a specific list of communication partners in a specific time period. Swarm behavior emerges as a result of communication between agents and individual control behaviors of agents [45].

Although this approach minimizes system operator interference and gives high priority to local behavior, agent behavior rules can be designed to prioritize signals from the system operator when necessary. In this approach, where distribution network control is distributed and its resilience against local faults and communication problems is increased, the system will still be operational in the event of a failure of a single unit [45].

5.2 Swarmgrid-X Concept

Due to the fact that the Swarmgrid algorithm can result in multiple communication partners for each agent, the hierarchical coordination-based Swarmgrid-X concept was born to overcome these potential communication problems. The main purpose functions of Swamgrid-X are local flexibility management and voltage control by managing active and reactive power flexibility. In this approach, communication takes place only between agents within a subgrid. If power cannot be adjusted in the sub-grid, the substation represented by an agent can communicate with other substation agents. If the substation agent has the appropriate flexibility, it can act as a producer. Moreover, if the agents of the subgrids are all consumers, they can communicate with the MV grid [44]. In Figure 5.1, the structure of Swarmgrid-X can be seen.

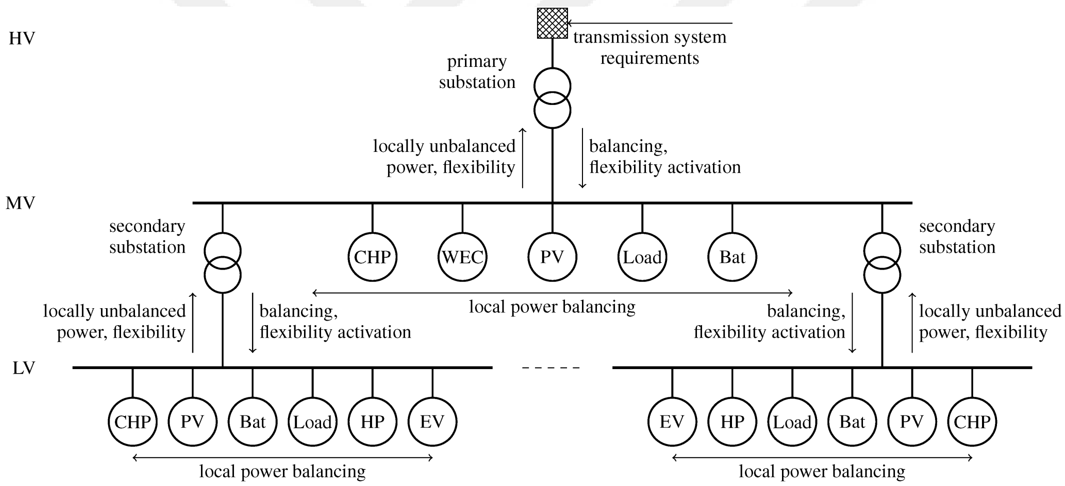

Figure 5.1 : Structure of Swarmgrid-X [44].

An agent exhibits a set of predefined behaviors in line with individual goals and can communicate directly with another agent in its swarm to influence the behavior of the other agent. Consumer agents try to meet their demands by finding a producer agent, while producer agents announce the amount of power they can provide to consumer agents. A swarm can grow or shrink according to various goals and situations.

In this concept, which is defined as holonic and can consist of sub-holons, the smallest unit is autonomous DERs, which can be power producers or consumers. These units come together to form holons in the upper layer, represented by a higher agent.

Negotiation between units in the same layer is possible, or the agent of the lower layer may seek help from the holons in the upper layers. In this way, the system becomes both fully distributed and hierarchical and more resilient to a local fault. Also, the disadvantage of the top-down approach, that the sub-units are directly affected by the errors that occur in the upper unit, is avoided [44]. In this approach, where information and power consumption are handled as local as possible, cooperation between agents is made to achieve the common system goal. This cooperation causes the distribution system to change from being a classical power system to a cyber-physical power system (CPPS) based on information and communication technology. Various negotiation protocols are presented in the Intelligent Physical Agents Foundation (FIPA) standards for managing communication between agents [44]. In the literature, there are studies examining the appropriate communication infrastructure for Swarmgrid applications for distribution networks [127]. However, within the scope of this thesis, the focus is mostly on the control behavior and negotiation processes between the agents.

In many MAS-based applications, agents' local control behavior is set as a global state variable, and system behavior is the result of all these behaviors. However, this can completely mislead the system behavior in case of potential errors in the negotiation algorithm. For this reason, the control behavior in Swarmgrid-X is completely based on local information and negotiations within the swarm, no global variables are taken into account. In this way, DERs are given the authority of control decision. The system in the proposed approach allows the creation of swarms of flexible agents that are compatible with the current electrical grid.

Within the scope of this thesis, legislative restrictions that may be necessary in real-world practice have not been taken into account. Similarly, it is assumed that data exchange regarding the necessary communication infrastructure is done in an appropriate and secure manner. The study focuses solely on the feasibility of integrating Swarmgrid-X into EV charger clusters.

5.3 Implementation of Swarmgrid-X to EV Charger Clusters

In the referenced study, the Swarmgrid-X algorithm uses distributed energy sources such as combined heat and power (CHP) power plants, electric heat pumps (HPs), wind energy converters (WECs), electric loads, photovoltaic (PV) generators, other than EVs was also taken into account [44]. However, in this thesis, as DER, we focused only on EVs. Swarmgrid-X, which offers an agent-based energy management concept, has been modified to improve effectiveness in V2X-capable clustered EV charging systems. A charger cluster is a collection of EV chargers controlled by a distributed energy management system. By bringing together flexible energy assets, local load balancing can be achieved within the EV charging clusters, thus enabling it to operate for a period of time without demanding electricity from the grid [128]. Figure 5.2 shows an example of a clustered charger system.

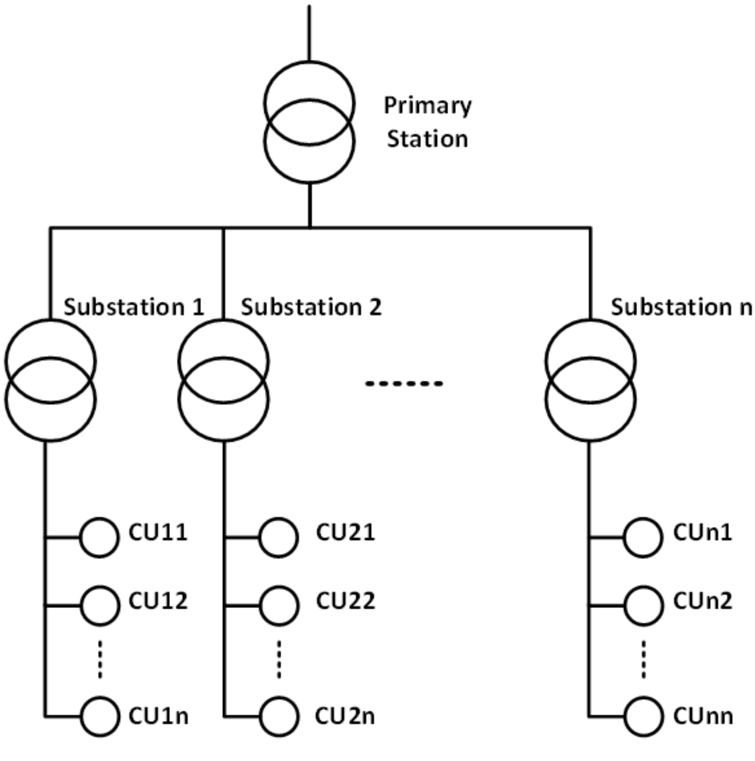

Figure 5.2 : Charger Clusters.

Each charging unit (CU) to which each electric vehicle in a charging station is connected is an agent with computational capability and can be assigned as a producer or consumer. The tolerances of the CU's represented by the agents are calculated in accordance with the urgency of the charging demands of EVs, and the agents are assigned as producer or consumer. They then communicate with other agents independently of a central unit, presenting each other the powers they can provide or the powers they demand. As a result of the negotiations between the two agents, power flow begins and power neutralization is attempted within the cluster.

In the next sections, how the role of the agent representing the CU to which each EV is connected is assigned at each moment, how an agent calculates the operation range, the flow of negotiation processes and finally the contracts between the agents are explained in detail.

5.3.1 The role of an agent

In the energy management concept presented in the thesis, the role of the agents representing the CUs to which the EVs are connected (which will also be used directly as EVs for convenience in the following steps) is updated at each time step. Two role options are possible for each agent:
- a consumer agent looking for a producer agent to meet the charging demand of the EV battery,
- a producer agent which can charge another EV by discharging its own battery.
Whether an agent is a producer or a consumer depends on its tolerance for interruption of charging. An agent with a higher tolerance acts as a producer as a more flexible energy asset. This tolerance value and role are determined based on the current and target SOC of the EV represented by the agent and the parking time. The parameter indicated as *m(t)* in Equation 5.1 is the tolerance of the agent and is calculated based on the charge demand of the EV and the power of the charger and the speed at which the demand is met.

$$m(t) = 1 - \frac{\frac{SoC(t_D) - SoC(t)}{P_{ch}}.E}{t_D - t} \tag{5.1}$$

The parameters SOC(t_D) and SOC(t) indicate the target and current state of charge (SOC) of the EV, respectively. E represents the energy capacity of the EV battery and P_{ch} represents the power of the charger. The parameter t_D shows the departure time when the EV reaches its target SOC, SOC(t_D) The tolerance indicated by *m(t)* is a dynamic value that is updated with each time step, expressing the agent's tolerance. A threshold value m_δ between 0 and 1 is determined. The fact that this value is greater than the m_δ indicates that the EV can tolerate the delay of charging for the calculated time step and can discharge its battery in that time, and this is a producer role that can perform V2X operation. On the other hand, if it is lower than m_δ,it indicates that the EV cannot tolerate it, and in this case, the agent is assigned as a consumer agent. In Equation 5.2, assignment of agent role according to a certain threshold is shown.

$$m(t) = 1 - \frac{\frac{soc(t_D) - soc(t)}{P_{ch}} . E}{t_D - t} \tag{5.2}$$

5.3.2 Operation range of an agent

Before the negotiation process between a producer and a consumer in the same swarm begins, both agents determine their active operation range. For this, the consumer agent calculates the power demanded from time t_1 to t_2 (as the contract period) and the producer agent calculates the power it can provide during this time.

In Figure 5.3, SOC change of two agents according to the operations, one of which is assigned as a producer and the other as a consumer, representing two EVs is shown as a simple example.

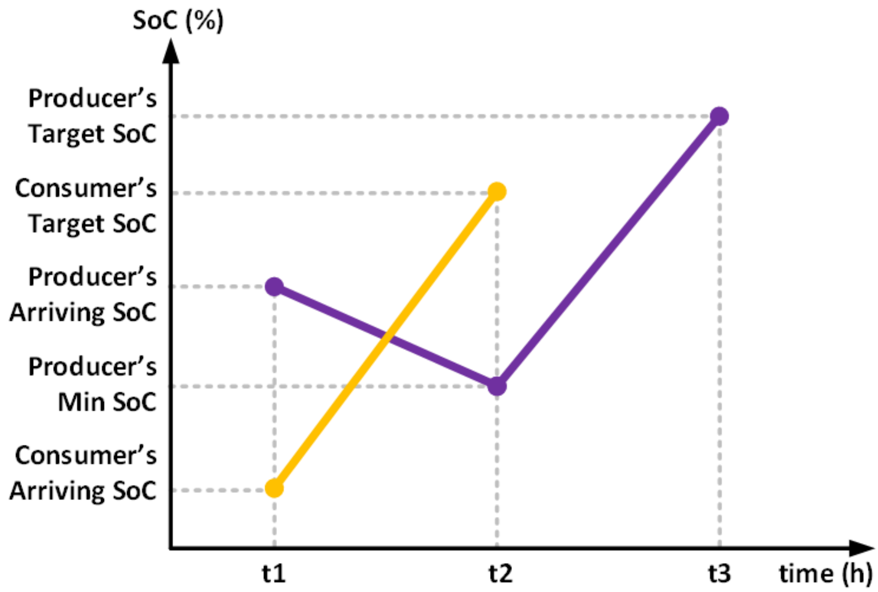

Figure 5.3 : SOC Change over Time of Agents.

The yellow line represents the agent assigned as a consumer at time t_1, and the purple line represents the agent assigned as a producer at time t_1. In the t_1-t_2 time interval, the producer agent discharges its battery and charges the consumer agent. It then charges itself in the range t_2-t_3 (from the grid or from another vehicle). In this case, in order for the producer agent to reach the target SOC until the moment of departure t_3, it must calculate the minimum SOC that it must have at the time of t_2.

Thus, the power demanded by the consumer agent in the t_1-t_2 time interval, P_c, is calculated as in Equation 5.3. Here, $SOC_c(t_2)$ and $SOC_c(t_1)$ represent the target and current SOC of the consumer agent, respectively, and E_c represents the energy capacity of the battery of the EV. The charging power can be as much as the power of the charger $P_{ch,c}$.

$$P_c = min\left\{P_{ch,c}, \frac{(soc_c(t_2) - soc_c(t_1)) * E_c}{t_2 - t_1}\right\} \tag{5.3}$$

The producer agent, on the other hand, must first calculate the minimum SOC that it can drop at the time of t_2, and then the power it can supply between t_1-t_2 accordingly.

As shown in Equation 5.4, the consumer agent's SOC at time t_2 is determined by the target SOC $SoC_p(t_3)$, the charging power $P_{ch,p}$, and the battery capacity of the EV battery E_p. Then, the power that the producer can provide in t_1-t_2 time period is calculated according to the current SOC $SoC_p(t_1)$ and min SOC $SoC_p(t_2)$ and battery capacity E_p, as in Equation 5.5. The power that the producer can provide can be as much as the power of the charger $P_{ch,c}$.

$$soc_p\left(t_2\right) = soc_p\left(t_3\right) - \frac{P_{ch,p}.(t_3 - t_2)}{E_p} \tag{5.4}$$

$$P_p = min\left\{P_{ch,c}, \frac{(soc_p\left(t_1\right) - soc_p\left(t_2\right)) * E_p}{t_2 - t_1}\right\} \tag{5.5}$$

These values are calculated continuously for each time interval. These agents, which can sometimes be producers and sometimes consumers, are called prosumer, which can produce and consume power. While making these calculations, the flexibility of users to participate in V2X operation was not included to the calculations, only technical calculations were made for the feasibility of the proposed EM approach.

5.3.3 Negotiation protocol

Agents negotiate based on their operation ranges. Since these negotiations are made for the operation ranges of each agent, individual targets are achieved and as a result of the negotiation global targets are also achieved, as local power balancing is achieved. Although these negotiations are always between two agents, an agent can negotiate with more than one agent for the same time step.

A consumer agent always initiates the negotiation. The consumer agent searches for a producer that will meet some or all of the power demand in its swarm of a series of consumer agents. Depending on the demand for this power, an agent's swarm can grow or shrink.

5.3.3.1 Directory facilitator

A Directory Facilitator (DF) is a service list or server that knows dynamically changing information and location of each agent type in all clusters. Types and locations of agents are information stored in DF. It can provide information to consumer agents looking for a producer when requested, but does not have any decision-making authority. This is not a central control unit. Also, DF does not know about other parameters of agents in the cluster.

A consumer agent which needs more producers to meet its demand or has not a producer in its swarm sends a message to DF. DF finds the producer agents at the specified distance and shares their information with the requesting consumer. In this situation, both agents add to each other's swarm. This is called the Recruiting Protocol.

5.3.3.2 Contracts between agents

The consumer agent sends a call for proposals to the producer agent that is in the swarm or that it has just added. If the producer can provide the desired power in the specified time, it accepts the offer of the agent and the contract is made. Thus, the negotiation is completed and the power flow begins. Otherwise, the producer sends a rejection message to the consumer and the consumer starts the search process again. If the consumer agent meets only a part of its demand from the producer agent, a contract is made again, but the consumer agent also looks for another producer to meet the remaining demand. An agent can have a contract with more than one agent at the same time. These negotiations are constantly updated with new parameters according to the power demand at each step. This processes is shown in Figure 5.4.

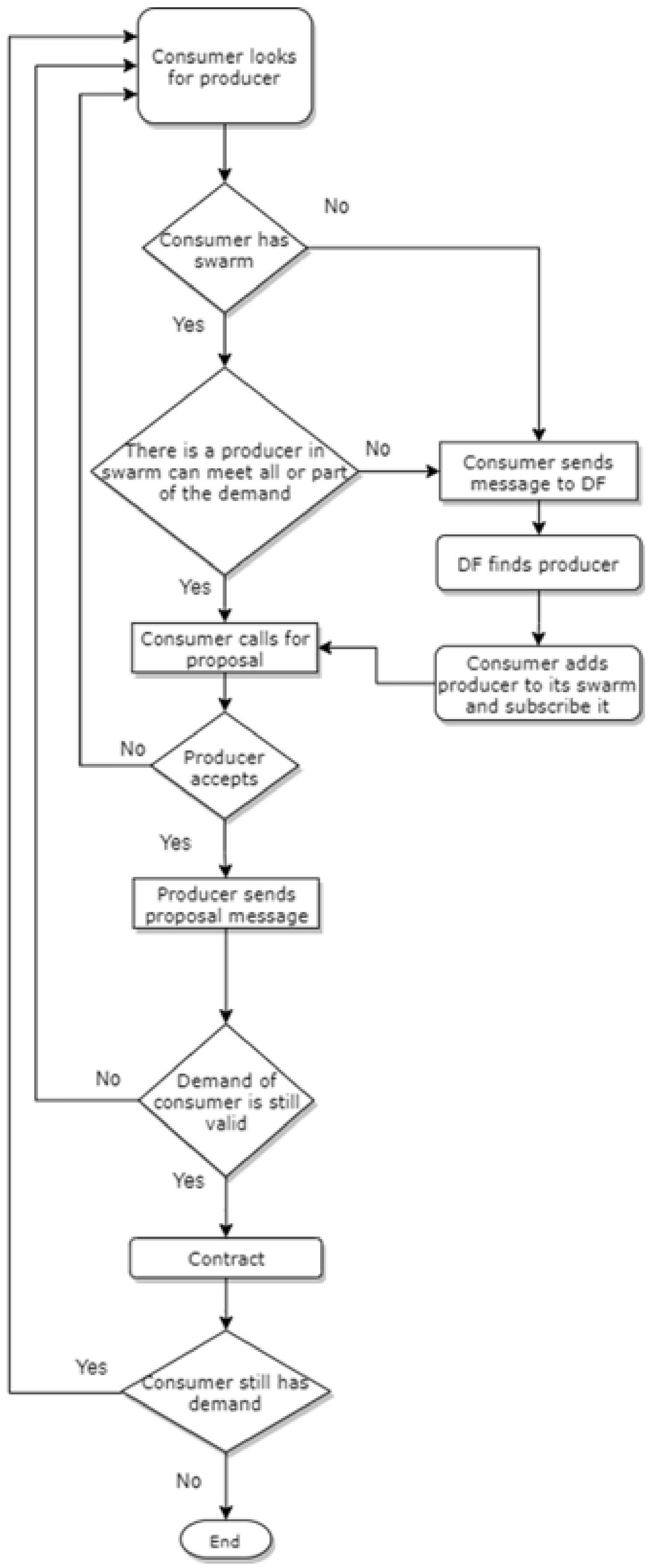

Figure 5.4 : Negotiation Protocol.

6. SIMULATIONS AND PERFORMANCE TESTS

This section discusses the details of the proposed approach. First of all, the effect of the tolerance threshold on the performance of the algorithm was investigated by comparing the simulations made with the proposed approach for different tolerance thresholds. Then, the performance of the proposed MAS-based approach compared to uncontrolled EV charging was evaluated.With this tests, it is aimed to observe the effects of approach to the peak to average power ratio of the charger cluster.

To evaluate the performance of the proposed approach, python programming language was used. With the object oriented programming approach, classes with various attributes and methods were created. Thus, an algorithm that can be easily adapted to different scenario situations was created. The UML diagram that summarizes how the algorithm works is given in the Figure 6.1.

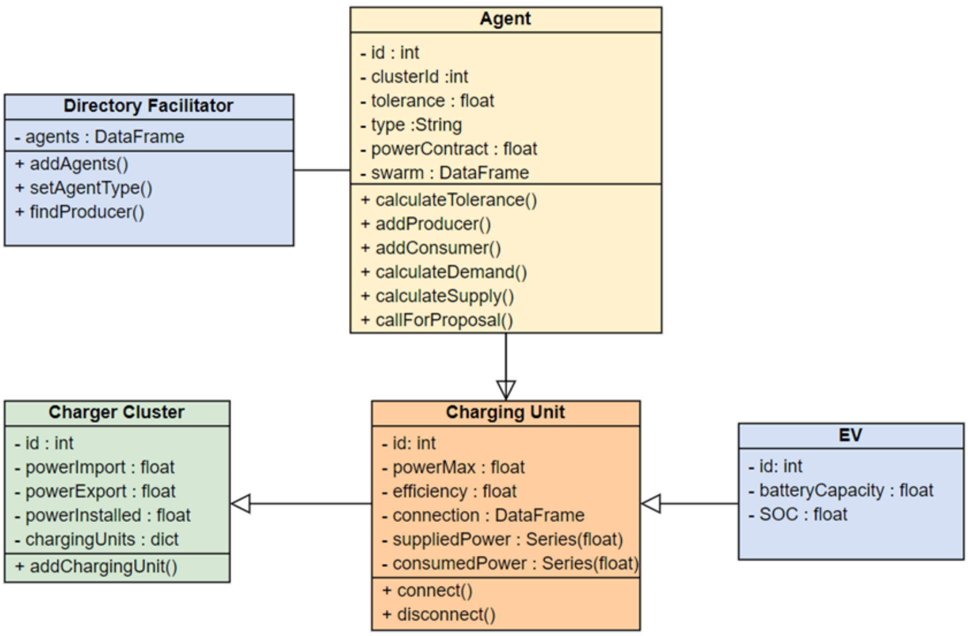

Figure 6.1 : UML Diagram of Proposed Approach.

The charging system in the scenario consists of charger clusters. Each EV arriving at the charging station at certain time intervals is randomly assigned to an available charging unit. As explained in the previous section, agents represent charger units. At each time step, the information of the agents in the Directory Facilitator is updated to include the new incoming EVs and to recalculate the flexibility of the existing agents. The current tolerance is calculated according to information such as the current and target SOC of the EV connected to the charger unit, the battery capacity and the duration of stay in the station. Depending on the tolerance threshold determined, agents take the role of producer or consumer. The consumer agent requests the producer information from the Direcitory Facilitator and creates a swarm according to its needs and starts negotiating.

6.1 Peak Power Reduction

The agent-based energy management algorithm presented in this thesis, which is an adaptation of the Swarmgrid-X algorithm, is applied to EV charging clusters. With this approach, it is aimed to increase the local load balancing capabilities within the charge clusters and to reduce the peak to average power ratio of the charge clusters. In the performance tests, the algorithm was applied in a scenario:

- 10 charger clusters containing 12 chargers of 11 kW each
- EV parking times ranging from approximately 1 to 6 hours
- EVs with 55 kWh battery with SOC varying between 20% and 80%
- Between 7:00 to 23:00
- Contracts renewed every 5 minutes

and the results were evaluated.In addition to the simulations performed by applying the proposed approach, the same scenario was also simulated and compared to uncontrolled operation. Figure 6.2 shows the power profile of a charger cluster under uncontrolled operation vs agent-based control approach applied with m_δ=0.50. Figure 6.3 shows, on the other hand, the power profile of a charger cluster under uncontrolled operation vs agent-based control approach applied with m_δ=0.75.

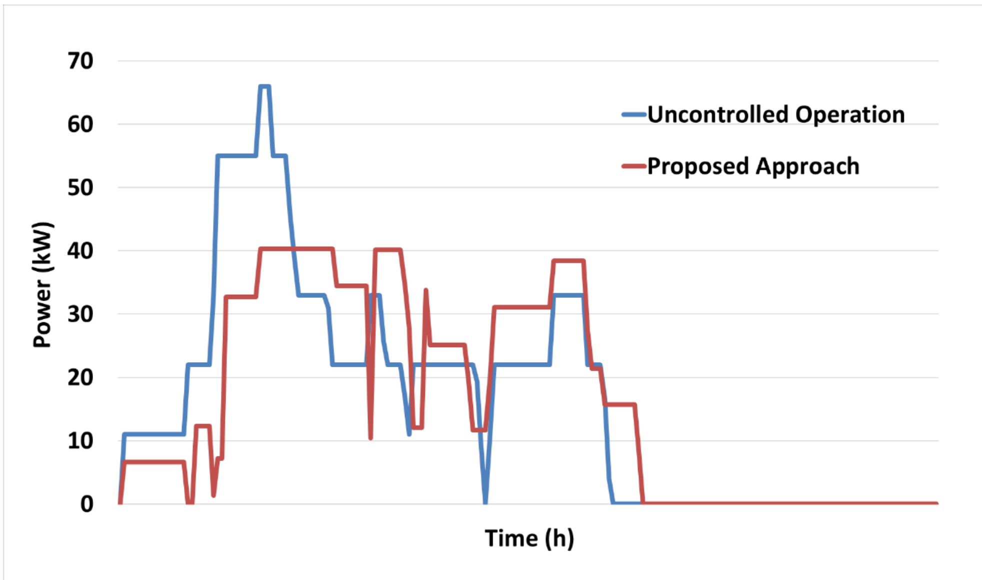

Figure 6.2 : Power Profile of a Cluster Uncontrolled Operation vs Proposed MAS-based Approach with tolerance threshold m_δ=0.50.

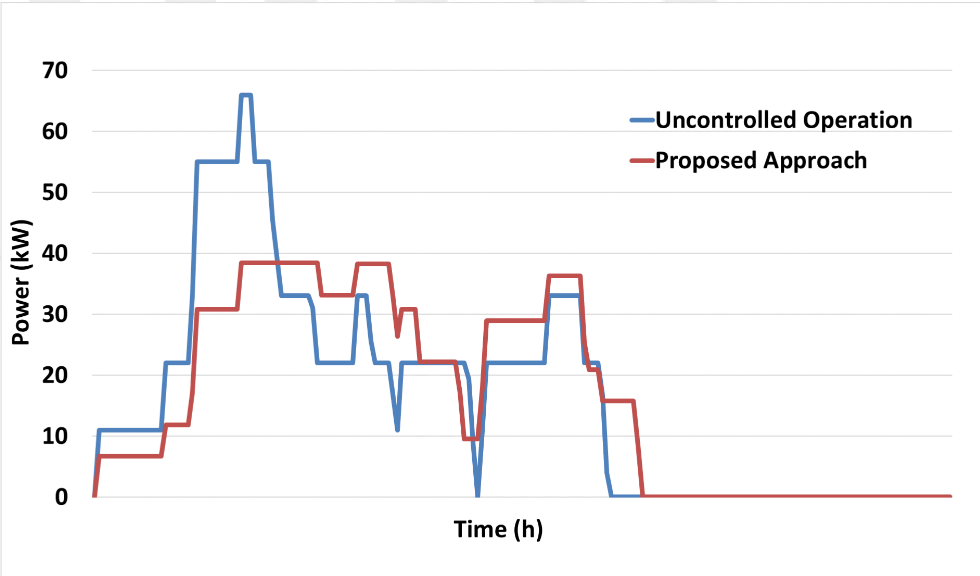

Figure 6.3 : Power Profile of a Cluster Uncontrolled Operation vs Proposed MAS-based Approach with tolerance threshold m_δ=0.75.

In Figure 6.2, agents with *m(t)* value greater than 0.5 are assigned producers, while in Figure 6.3, agents with *m(t)* greater than 0.75 are producers. In the first case, the peak power demand in the cluster decreased by 39%, while in the second case it decreased by about 42%. Here, a better result is seen in case of higher m_δa determination, although fewer agents are assigned as producers. Thus, less V2X operation resulted in a better power profile. Although the reason for this is explained in more detail in the following, in the first case (Figure 6.2) consumption is delayed too much and then again causes peaks.

The power profile in cluster 10 for different values of m_δ is shown in Figures 6.2 and 6.3. However, the performance of the algorithm also depends on the demands and charging durations of the vehicles connected during the scenario period. For this reason, the improvements are not identical in all cluster and such significant changes were not seen.

As explained in detail in the previous section, the *m(t)* value indicating tolerance determines the role of an agent. Agents whose tolerance is above the determined value of m_δ are appointed as producer agents. When the same simulation was performed for different m_δ threshold values, the peak and mean values in Table 6.1 were obtained. These results were calculated for all 10 clusters, i.e. the whole system, and were compared with the situation where the m_δ is 1, that is, there is no producer.

Table 6.1 : Peak to Average Ratio Comparison.

	Benchmark m_δ=1.00	m_δ=0.75	m_δ=0.50	m_δ=0.25
Peak (kW)	351.5	335.2	357.1	379.3
Average (kW)	150.5	150.5	150.5	150.5
Peak/Average Ratio	2.33	2.22	2.37	2.52

As can be seen in the Table 6.1, it is clear that the algorithm depends on the tolerance value m_δ. For a higher value of m_δ, it is more difficult to appoint agents as producers. In this case, the value of m_δ=1 is the same as the uncontrolled case where no agent is a producer and there is no V2X operation.

On the contrary, in case of smaller m tolerance threshold, more agents are producers, that is, local power balancing is achieved since more EVs participate in V2X. In this case, it will be expected that the peak loads in the cluster will decrease more. However, as can be seen from the table, choosing a lower m_δ value does not always result in a lower peak powers. For example, while the peak power measured for m_δ=0.75 is 335 kW, higher peak powers have been measured in the simulations at m_δ=0.5 threshold value, and it is seen that these peak powers are even higher than the uncontrolled operation's power value. The reason for these high peak values is explained by giving an example from the power profile of a different cluster (7th cluster) as shown in Figure 6.4.

Choosing a small value of m causes more agents to be producers at time t, and they charge other EVs by discharging in time T. Then, at t+T, they need to recharge themselves as consumers. In this case, the number of EVs whose charges are delayed to t+T time will be much higher and very high peak demands will be seen at t+T time. The most dramatic example of this is seen in the power profile of 7th cluster. In the simulation performed with a tolerance value of m_δ=0.25, it is clearly seen how the charging delayed at the beginning of the simulation results in a peak demand later on.

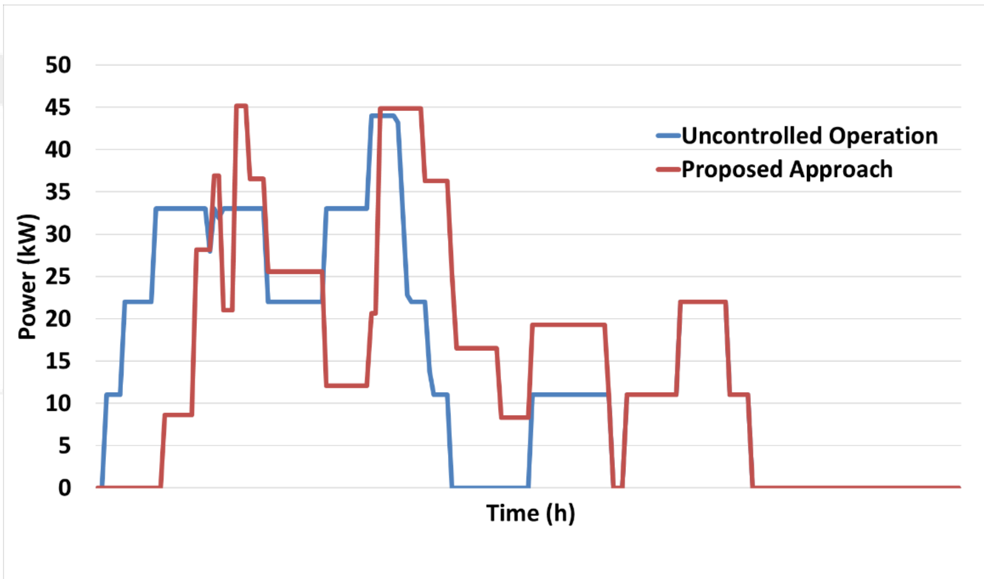

Figure 6.4 : Power Profile of 7th Cluster for tolerance threshold m_δ=0.25.

The impact of many unpredictable variables in the scenario, such as arrival times of EVs, current and available SOCs, and parking durations is also very significant. In order to avoid high peak demands, a prediction can be made and a control algorithm can be developed based on the past power demand profiles of the clusters and the system. In this way, potential problems caused by this randomness can be avoided. Based on the estimations, if different m values are assigned to each instant of t, more producers can be assigned in case of simultaneity of power demand and balancing can be performed much better with V2X operation at the right time.

In order to evaluate the performance of the agent-based approach in different scenarios, the peak-to-average ratio distribution of 10 different charger clusters in 20 different scenarios is shown in Figure 6.5. The green dots show the uncontrolled approach, while the orange dots show the results when the energy management approach is applied. The uncertainties in the scenario such as arrival and departure times of EVs, target and current SOC may cause the result not always to turn out better when the energy management approach is applied. However, in most of the scenarios, it is observed that the performance of agent-based energy management shows better results. In the uncontrolled condition, the peak-to-average ratio increases up to 4.65 in the simulations, while it is seen that it is at most 3.76 with the proposed approach.

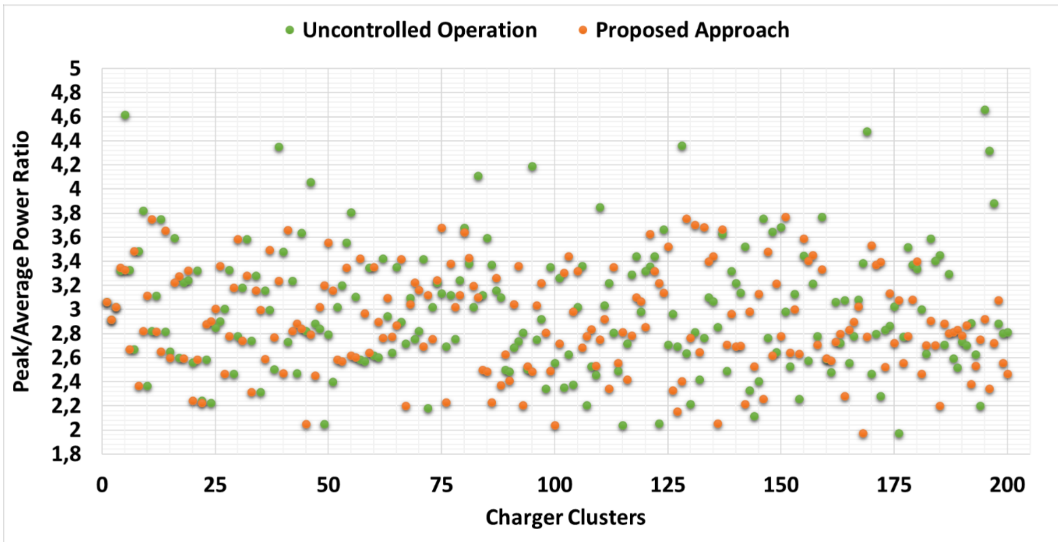

Figure 6.5 : Peak to Average Ratio Distribution.

6.2 Scalability

In this section, the computational performance of the algorithm has been tested without considering the tolerance value m and other variables, unlike the above evaluations. The time required to converge to the solution is calculated by increasing the number of agents in the cluster. In simulations, agent roles, negotiations and contracts are updated every 5 minutes. However, if the number of agents in the scenario is less than 125, it is seen that the solution can be converged in 60 seconds. This is important for a practical application. For this reason, a period of 60 seconds can be selected as the scalability threshold.

Since the increase in the number of agents results in more negotiations, the computation time also increases in parallel. However, the increase in the number of clusters does not cause any change in the scope of the application in this thesis. This is because negotiations only take place within the cluster. For this reason, these processes that clusters carry out in parallel do not cause an additional computational burden.

7. CONCLUSIONS AND RECOMMENDATIONS

In this thesis, SwarmGrid-X, an agent-based energy management algorithm, has been adapted and implemented for clustered EV charging systems. In the proposed approach, depending on the urgency of the charging demands of the EVs connected to the chargers and the tolerance threshold in the algorithm, the agents representing the charger units are assigned the role of producer or consumer. Agents in the consumer role get the location of producers through a server called DF, add them to their swarm and negotiate. If the negotiation results in a contract, power flows for the specified contract period. In this way, the producer agent discharges, meeting the charging demand of the consumer agent.

The performance evaluation in the thesis was made by applying this approach to a system consisting of 10 charger clusters, each with 12 charging units. Power profiles of uncontrolled operation and proposed approach were compared. With the appropriate m_{δ} selection, the proposed MAS-based approach has been shown to reduce the peak-to-average ratio of a cluster by up to 42%. As a result of the simulations made with this approach, a positive effect on the power profile of the charger clusters was observed when EVs stoped to be local consumers and became electricity producers with V2X operation. On the other hand, the effect of different tolerance values on the performance of the algorithm is also discussed. Computational analysis showed that the computational load of this algorithm is directly related to the number of agents in the cluster.

It has been observed that units called agents can take adequate control decisions with limited local information. Without the need for a central control unit and without information of the grid or the cluster, agents can neutralize the cluster in line with their individual goals. Agents were able to exchange power by negotiating with each other with very little communication overhead compared to other approaches in the literature. This demonstrates the feasibility of an agent-based approach without any centralized control.

In addition, while the profile of EVs connected to charging units is identical in many other applications, the charging demands of EVs are variable in this thesis and the flexibility of EVs for V2X is also variable. In the simulation scenario, the number of EVs connected to a charging unit during the simulation period, the arrival and destination SOCs of the EVs are completely random. This means that in any scenario, the role of a charging unit to which different EVs are connected is updated at each time step, negotiating with other agents in the cluster for negotiation.

With this energy management algorithm, unlike previous studies, bidirectional charging is handled. Thus, it is aimed to use the V2X functions in the most effective way and to use the EVs efficiently in their idle time. Thanks to the V2X function, the peak power demand in the clusters and the overload of the charging units on the grid have been reduced.

7.1 Recommendations and Future Work

For future studies, it is recommended to assign agents representing the total behavior of each cluster so that this power balancing within the cluster can be also done between clusters. In this way, in case the demand is not met within the cluster, it can request power from another cluster instead of requesting it directly from the grid. However, in such an application, the computational burden of negotiating between clusters should be taken into account.

Another improvement to be made is to make the m_{δ} value dynamic for each time step t, allowing it to adapt depending on the demand of the clusters and the variability of the EVs in the cluster. Thus, peak levels can be minimized and the load profile can be flattened.

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