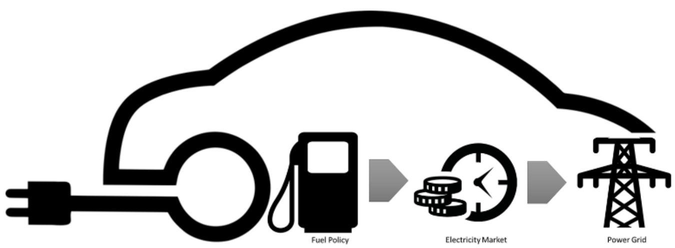
# Electrification of Transportation: From Fuel Policy to Electricity Market and EV Battery Charging in Microgrids

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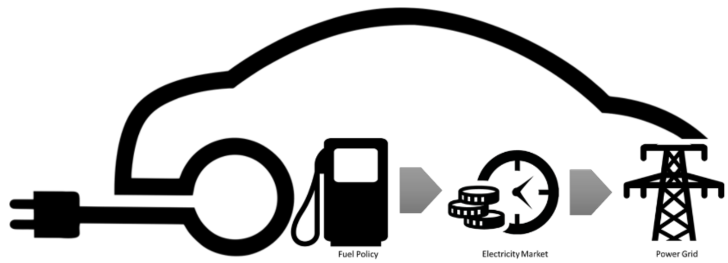


Ahmad Karnama

Thesis for awarding Doctor of Philosophy degree in Sustainable Energy Systems from MIT Portugal Program issued by Faculty of Engineering University of Porto in Porto, Portugal.

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*To my best friend and the kindest wife, Alaleh*

*To my dearest parents, Mohammadreza and Forough*

## Abstract

Electric Vehicles (EV) are increasing the interdependence of transportation policies and electricity market and power grid. From transportation policy perspective, most policies incentivize low carbon transportation. From electricity market perspective, the growing number of EVs will increase the electricity load and eventually can influence the price of electricity. From power grid perspective, the load from EVs can influence the load and voltage at all voltage levels. This thesis aims to discuss how the clean energy transportation policies can influence the electricity market structure and electricity prices, and on the other hand, how the load from EVs can influence the power grid and how the future power grid should manage the EV load.

Electricity Market Model with Electric Vehicles (EMMEV) is a testing platform to analyze the impact of different low carbon transportation policies on electricity market. It is an agent-based model in which the agents are Energy Service Companies (ESCos). In this thesis, EMMEV is used to investigate the impact of implementation of an Low Carbon Fuel Standard (LCFS) as a policy driver for increasing the use of low carbon vehicles on the electricity market.

Low Carbon Fuel Standard is a market-based policy driver in which the players are fuel distributors, and the regulators set a long-term goal for carbon reduction in transportation. At the end of each year, based on the carbon intensity of their fuel sold, the players are either eligible to get a certificate or are obliged to buy a certificate. This makes a market environment in which the players can gain by selling more low carbon fuels.

The results of the modeling show that the banking strategy of the agents contributing in LCFS can have negative impact on penetration of EVs, if there is no less regular Credit Clearance happening and a price cap is set by the regulators. The electricity price as result of implementing LCFS and increasing number of EVs is between 2-3 percent, depending on banking strategy.

The Micro Grid (MG) concept can be implemented to support the progressive integration of EVs into the Low Voltage (LV) networks by developing smart charging strategies to manage the EVs' batteries charging to avoid the reinforcements of grid infrastructures. If several EV owners allow the charging of their batteries to be managed while their cars are parked, this thesis proposes an approach that aims to find suitable individual active power set-points corresponding to the hourly charging rate of each EV battery connected

to the LV grid. The Evolutionary Particle Swarm Optimization (EPSO) tool is used to find these active power set-points. This requires an additional software module to be housed in the MV/LV secondary substation level, called Optimal Power Set-points Calculator (OPSC).

*Index Terms*—Smart Grid, Electric Vehicles, Agent-based modeling, Electricity market modeling, Power Grid, Electricity Market, Micro Grid, Transportation Policy

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My PhD has been a journey of learning and enjoyment. Not only I feel that I acquired the hard skills to be a thoughtful and expert researcher, but I believe I learnt a lot from the soft skills as well. I entered Porto for the first time in my life on 25 May 2010 with the ambition to become successful researcher. Now after 10 years that I am planning to earn my PhD, I successfully managed to structure my thesis and publish my papers while I was in Stockholm. I managed to get funding for my PhD from my own company and develop my research. This cannot happen without super kind family and super supportive supervisors.

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Ahmad Karnama
July 2020, Täby, Stockholm, Sweden

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## Acronyms and abbreviations

| | |
|---|---|
| **ABM** | Agent-Based Modeling |
| **BEV** | Battery Electric Vehicle |
| **CI** | Carbon Intensity |
| **DSO** | Distribution System Operator |
| **DER** | Distributed Energy Resources |
| **EMMEV** | Electricity Market Model with EVs |
| **EPSO** | Evolutionary Particle Swarm Optimization |
| **ESCo** | Energy Service Company |
| **EV** | Electric Vehicle |
| **EVI** | Electric Vehicle Initiative |
| **EX.0** | ENERGY X.0 |
| **FiT** | Feet-in-Tariff |
| **LBR** | Load Balance Responsible |
| **LCFS** | Low Carbon Fuel Standard |
| **LCV** | Low Carbon Vehicle |
| **LDV** | Light Duty Vehicle |
| **LV** | Low Voltage |
| **MET** | Model for Electrification of Transportation |
| **MC** | Mobility Credits |
| **MG** | Micro Grid |
| **MGCC** | Micro Grid Central Controller |
| **MV** | Medium Voltage |
| **OPSC** | Optimal Power Set-points Calculator |
| **PED** | Price Elasticity of Demand |
| **PHEV** | Plug-in Hybrid Electric Vehicle |
| **PLDV** | Passenger Light Duty Vehicles |
| **PPA** | Power Purchase Agreement |
| **RCM** | Renewable Certificate Market |
| **SGAM** | Smart Grid Architecture Model |
| **SWOT** | Strength, Weakness, Opportunity and Threat |
| **SOC** | State Of Charge |
| **ToU** | Time of Use |
| **VC** | Vehicle Controller |
| **VPP** | Virtual Power Plant |

# Chapter 1
# Introduction

It was a German inventor, Nikolaus Otto, who first made it possible to use combustion engines in cars by the invention of the first four-stroke internal combustion engine in 1862. This type of engine is continuously being used in so-called conventional vehicles. The low-efficiency of Internal Combustion Engines (ICE) and high emission production are the main drawbacks of driving this type of vehicle.

Between 1889 and 1890 EVs have outsold ICE vehicles in the US. Electric vehicles had many advantages: less vibration, smell and noise from the gasoline-powered cars. The main disadvantage of ICE vehicles was the external starting the vehicle which was difficult, dirty and dangerous; EVs don't need external starting. In addition, changing gears was problematic and this was resolved in in electric vehicles. But the electric car declined in popularity. There were three main reasons: 1. Longer range vehicles were needed due to better roads that connected cities. 2. Reduction of gasoline price due to discovery of oil in Texas. 3. Hand cranks were not anymore required since Charles Kettering in 1912 discovered electric starter [1].

One of the most important breakthroughs in the car industry after Otto's invention was the transition from conventional vehicles to 'hybrid' electric vehicles (although there had been an early wave of EVs before). This type of vehicle was first introduced in 1997 in Japan through the Toyota Prius. One of the main specifications of them is the operation of the ICE on its efficient interval by means of a regenerative braking system while the combustion engine is combined with a battery and electric motor. The following figure shows the recent development of the car industry:

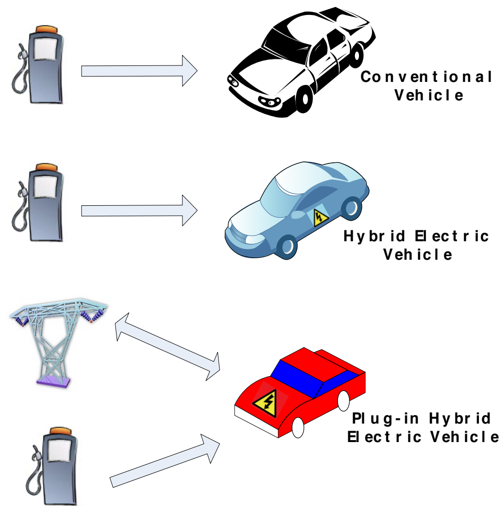


**Figure 1: Development of the car industry**

Electric Vehicle is a generic term which, in this thesis, refers to any type of battery vehicle with charging capability from the power grid. This includes Plug-in Hybrid Electric Vehicle (PHEV) which has both a conventional engine and battery (electric generator) inside and Battery Electric Vehicle (BEV), which is basically a pure Electric Vehicle. These are the next generation of vehicles which are gradually coming on the market. Their main specification which makes them different from other types of vehicles is their capability to be charged from the power grid. The main drivers to introduce Electric Vehicles (EVs) are increasing price and lack of fossil fuel resources, increasing electricity generation from renewable resources and high emissions from conventional vehicles.

More than 27 percent of the world total final energy is consumed in the transport sector, of which more than 95 percent is fossil fuels. In addition, around 35 percent of total fossil fuels in the world is consumed in the transport sector [2]. High prices of fossil fuels, political volatility in the countries with large fossil fuel resources together with high emissions produced from fossil fuels have pushed decision makers to look for new energy alternatives. In this context, the transport sector has considerably high potentials to decrease fossil fuels dependency [3].

In 2017, 1.1 million EVs were sold globally (a world record and increase of 54% reference to 2016), leading to a global stock of over 3 million. China accounted for nearly half of electric car sales, with Norway having the highest per capita ownership [4].

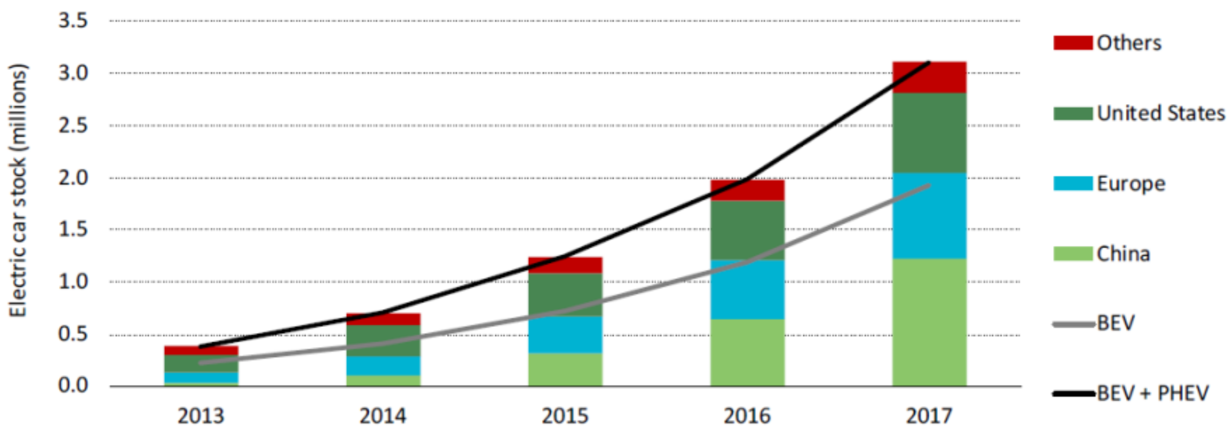


**Figure 2: Evolution of the global electric vehicle stock [4]**

The future of Electric Vehicles is evaluated in the International Energy Agency report. There are two main scenarios which are investigated:

- The New Policies Scenario (NPS) is the central scenario of the IEA's World Energy Outlook. The scenario incorporates the policies and measures that governments around the world have already put in place, as well as the likely effects of announced policies that are expressed in official targets or plans.
- The EV30@30 Scenario, which is consistent with the ambitions pledged by EVI (Electric Vehicle Initiative) countries[1] in the EV30@30 Campaign Declaration (CEM-EVI, 2017 [5]). In this scenario, the EV30@30, which target the 30% market share of EVs for LDVs, buses and trucks collectively – is met at the global level.

[1] Governments currently active in the EVI include Canada, the People's Republic of China ("China"), Finland, France, Germany, India, Japan, Mexico, Netherlands, Norway, Sweden, United Kingdom and United States. This group includes the largest and most rapidly growing EV markets worldwide and accounted for the vast majority of global EV sales in 2017. Canada and China are the co-leads of the initiative. The International Energy Agency serves as the EVI coordinator.

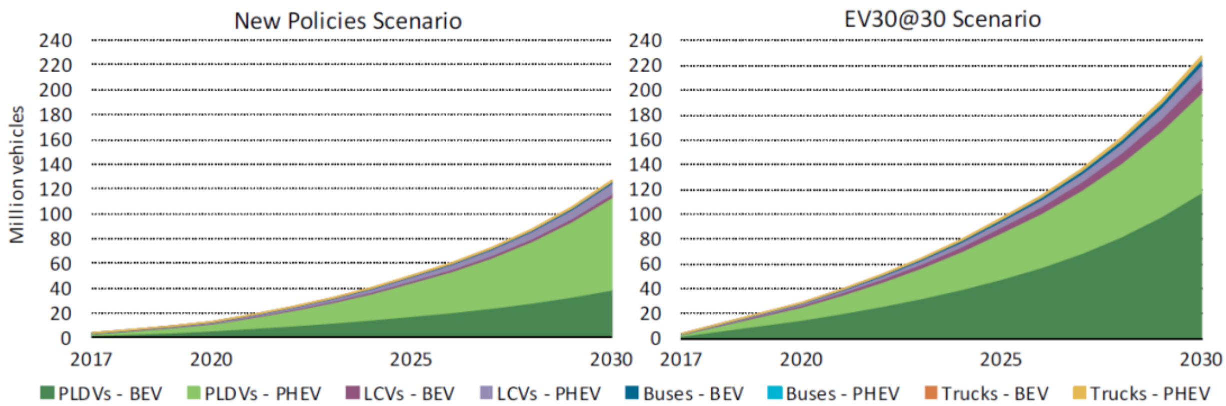


**Figure 3: Global EV stock by scenario, 2017-30[2] [4]**

The increasing number of EVs will create a potential for using the power from the EV's battery in the grid for resiliency purposes. Table 1 classifies 4 types of grid resilience services that seem to be thoroughly associated with each of the three modes of EV integration. Some services utilize more than one mode of integration, such as frequency regulation which is common to both Vehicle to Grid (V2G) and Grid to Vehicle (G2V). Other services are exclusive to a mode, such as back-up generation, where EVs can be used to power homes, hospitals and institutions, thereby reducing the fatalities and cost of power disconnection [6].

**Table 1 Types of grid resilience services from Electric Vehicles [6]**

| | Type of Service | | | |
|---|---|---|---|---|
| Grid-to-Vehicle (G2V) | Demand Response | Valley Filling | Negative Demand Response | Frequency regulation |
| Vehicle-to-Building (V2B) | Emergency back-up | Demand Charge Reduction | Reserves | Negative Demand Response |
| Vehicle-to-Grid (V2G) | Voltage control | Frequency regulation | Reserves | Capacity Firming |

The size of impact of any of the above grid resilience services are summarized in Figure 4.

[2] LCVs = light commercial vehicles; BEVs = battery electric vehicles; PHEV = plug-in hybrid electric vehicles.

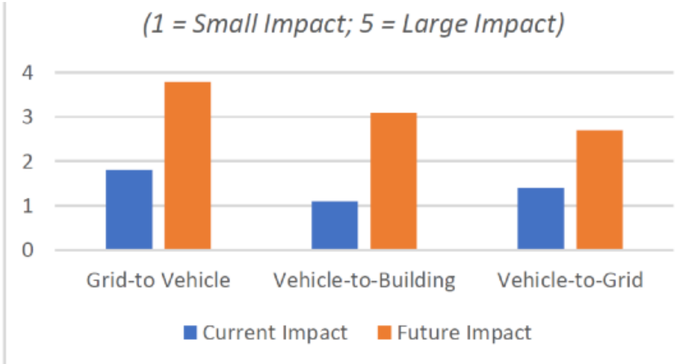


**Figure 4: The overall potential impact of various modes of EV [6]**

The integrated analysis and the actual data for 2017 done by Aman Verma [7] find that a typical mid-size EV produces up to 67% lower GHG emissions than a gasoline ICE car on a well-to-wheel basis, contingent on where they are driven. The largest savings of global CO2 emissions related to electric vehicles are largely in China (81%) where the number of 2-wheelers is high, even though power generation is carbon-intensive. This has been shown graphically in Figure 5.

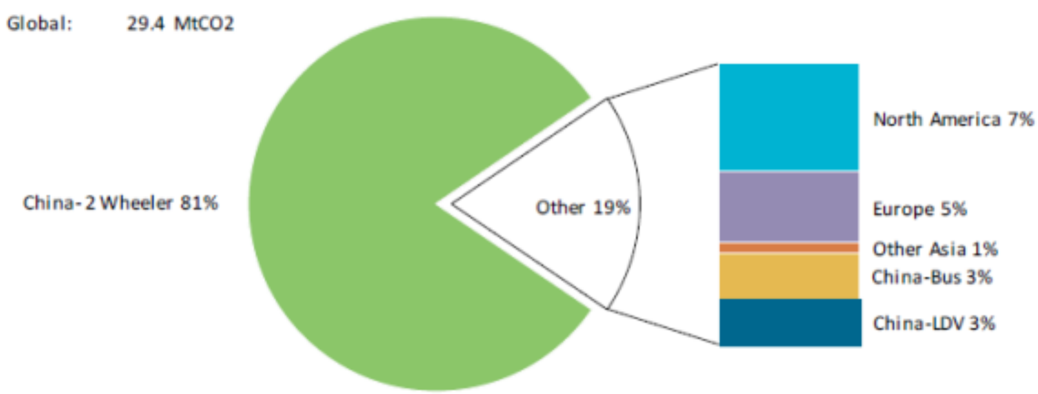


**Figure 5: Avoided $CO_2$ emissions due to EVs in 2017[3] [4]**

Several fuel alternatives for vehicles including electricity exist in the market but they still have a low share of the vehicle market. EVs have a chance of taking a larger share of the future market. However, apart from high vehicle price which is still the main barrier, policies are not yet motivating enough, and business models are primitive. After a phase of research on feasibility

[3] LDV refers to light-duty vehicle. Unless stated otherwise, emissions savings refer to the entire EV fleet.

analysis of large scale deployment of EVs [8] [9] [10], it is now important to develop business models and start the planning for the take-up of EVs in transportation.

In [11], the author tries to model the EV market, taking into account the spatial and social effects without considering the technical charging issues. In [11] a desirability factor for vehicle drivers to change to a new vehicle is introduced. This factor specifies whether the conventional vehicle driver decides to change his or her vehicle to a new vehicle alternative or not. The desirability factor is influenced by two general concerns of the drivers: financial and non-financial (as with environmental issues). The vehicle drivers will change their vehicle between a Gas Vehicle (GV), Hybrid Electric Vehicle (HEV) or Plug-in Hybrid Electric Vehicle (PHEV) if their desirability factor reaches a certain point. Electrification of transportation is an alternative which needs to be promoted. Some studies has investigated the effects of the incentives like in [12]. This thesis presents a model for EVs' penetration and investigates the effects on the electricity market.

The electricity market is where the generation units and retailers trade electricity. This market is introduced after the liberalization in the power systems. The liberalization occurred since promotion of the electricity sector was adopted to induce competition and therefore efficiency. The generation units set their bid price to cover their operational cost. Based on bid prices and amounts and consumption levels, the market price is set. Those players with lower bid prices than the settled market price succeed to sell their electricity. The prices are set in hourly based (15-minute basis in Australia and California) and the players are free to form forward contacts (long-term contracts). This structure is implemented in most of electricity markets around the world (like in NordPool in Scandinavia and MIBEL in the Iberian Peninsula).

Trading in electricity markets can be obtained via:

- Bilateral contracts – Contracts between the generators and retailers or eligible/large customers in a direct way in which prices, electricity demand and generation are set for a period of time.

- Centralized electricity markets – Mechanisms that obtain an economic schedule based on the clearing of the buying and selling electricity bids.

Electricity markets play an important role in the integration of EVs to the power grid. The current models used in research and industry for this market [13] [14] are pretty advanced but the position of EVs is either not considered properly or the models of electricity market with EVs are still simple or the role of EVs management actors (EV aggregators) are not defined adequately. ESCos (Energy Service Companies) are existing players in the market which can act as EV aggregators in the future. An ESCo is a commercial or non-profit business providing a broad range of energy services including designs and implementation of energy savings projects, retrofitting, energy conservation, energy infrastructure outsourcing, power generation and energy supply, and risk management. In this thesis, the term ESCo is used to act also as EV aggregator.

In this thesis, the behavior of EV drivers is assumed to be the same as that of conventional vehicle drivers. This assumption, with an accurate approximation, will make it possible to use the existing data from conventional vehicles to model the EV drivers' behavior. This behavior can be mathematically modeled as it has been done in [15]. However, the way it is expected that EVs will be charged will have a significant influence on EV load diagram of the system – and eventually on the formation of the price markets.

A model for the electricity market that includes Electric Vehicles aggregators is developed in this thesis and it is investigated how ESCos can make profit from offering EV aggregation services to the customers. This includes the mechanism how to manage the EV's load as well as defining possible streams of revenue for EV aggregators.

This thesis starts by research questions and then state of the art and objectives are presented. After an introduction, the proposed methodologies are described. Then a test system is presented, and the results based on the developed model called Model for Electrification of Transportation (MET) are presented.

## 1.1 ENERGY X.0

Climate change is an existential threat to all of us and the energy sector is primarily responsible. There has been a long debate whether climate change is real or not. I believe that the scientific proofs to support the climate change are undeniable, but the concerns of those whom deny climate change must be considered [16]. To have truly neutral judgment, the risk of such a threat must be calculated. To calculate the risk of any threat, the severity is multiplied by its likelihood. Even if the likelihood of climate change is very low (based on the opinions of those who deny climate change), the risk is still very high due to the extreme level of severity. This is a global threat, and nobody is safe if it is real. Therefore, energy sector is in need of a revolution to save our planet. On the other hand, technological progress is at a tipping point where such revolution is no longer a cost; in fact, it makes reasonable returns on the investments. Energy X.0 encapsulates the visions for such a revolution in the energy systems, considering technological progress and the need for a revolution to save our planet. The target groups for such a revolution are three main groups:

1. Utilities
2. Large Energy Consumers
3. New Players

Utilities are convectional energy providers and their primary interests are to provide reliable energy services, maintain their market position, and even expand their business [17]. Large Energy Consumers are referred to large industries or groups of smaller energy consumers. Their interest is to maintain, or even increase, their security of supply and decrease their costs and dependency on utilities. The New Players in the energy market are referred to opportunistic SMEs. Their interest is to serve the needs of energy consumers and bypass utilities, or at least stop them from further expansion into new business opportunities [18]. Energy X.0 has four pillars, as shown below:

1. Renewable Energies
2. Sustainable Transportation
3. Local Energy System
4. New Energy Solutions

In the next sections, a Strength, Weakness, Opportunity and Threat (SWOT) analysis for the three pillars in four pillars of ENERGY X.0 is performed. SWOT analysis is a framework used to evaluate a company's (in this thesis, the three players introduced above) competitive position and potentials for future growth. SWOT analysis assesses internal and external aspects, as well as current and imminent potential.

### 1.1.1 Renewable Energies

A desert of 1 million $km^2$ (equal to almost twice the size of Sweden) covered with solar panels can generate 1000 times the total energy requirements of Europe. This is an opportunity for utilities, Large Energy Consumers, and New Players to gain as much as possible from these type of free energy resources [19]. However, there are challenges as well which are introduced in the following table.

**Table 2 SWOT Analysis for Renewable Energies**

| | Strength | Weakness | Opportunity | Threat |
|---|---|---|---|---|
| Utilities | Established market position | Low organizational agility | Potential for market expansion | Loss of market share to the New Players |
| Large Energy Consumers | Asset ownership | Lack of knowledge | Energy cost reduction Reduction of dependency on utilities | Loss of business focus |
| New Players | Organizational agility | Need of capital and reputation | Easy market entry due to blue ocean | Changing market environment |

Through technology advancements and the reduction in the price of technologies, the returns on renewable investment are becoming much more reasonable than before. Utilities can invest in renewable power plants and not only contribute to a low-carbon society, but also receive reasonable returns on investments. The Large Energy Consumers can be part of those investments in distributed energy generation units. Not only can they get a return on their investments but also gain independency from utilities (this will be described in more detail in the Local Energy System section).

In this environment, New Players can enter the market much easier than before. The size of investment on a distributed generation unit (like solar or wind) can be a fraction of the larger power plants. In addition, the knowledge in this area is still fresh and easier for the New Players to learn.

### 1.1.2 Sustainable Transportation

About 36% of the total energy consumption in the world is in the transportation sector; in total this sector is responsible for 20% of emissions. Any vision for the future of energy systems without considering transportation is incomplete. Electrification of transportation, fuel cells, and green fuels are among the most mature alternatives for the future of transportation.

**Table 3 SWOT Analysis for Sustainable Transportation**

| | Strength | Weakness | Opportunity | Threat |
|---|---|---|---|---|
| Utilities | Established connections | Unknown market position | Potential for new business opportunity | Loss of business focus |

| | | | | |
|---|---|---|---|---|
| Large Energy Consumers | Asset ownership | Lack of knowledge | Contribution of low-carbon society and green branding | Higher costs |
| New Players | Organizational agility | Low access to capital | High long-term potentials | Low short-term return on investment for cash-constraint players |

Utilities can act as a distributor of energy for transportation. In the e-mobility sector, utilities have already placed themselves as aggregators for changing stations. However, gaining short-term profitability from such a market is still difficult.

### 1.1.3 Local Energy Systems

Increasing energy generation from distributed resources makes it possible to have local energy systems. Central energy systems were necessary when the large power plants supplied energy. Nowadays, energy consumers can be 'prosumers' and can go one step further to own their own local energy system.

A Local Energy System or a Micro Grid consists of a group of energy consumers, generation units (mainly renewables), storage, and control systems to operate a section of the power grid independently of the main grid at least part of its operation time.

**Table 4 SWOT Analysis for Local Energy Systems**

| | Strength | Weakness | Opportunity | Threat |
|---|---|---|---|---|
| Utilities | Access to end consumers | Lack of innovation ecosystem | Potential for new business opportunity | Expose to competition |
| Large Energy Consumers | Asset ownership | Lack of knowledge | Contribution of low-carbon society | Higher costs and immaturity of the technology |
| New Players | Organizational agility | Low access to capital and past experiences | Create an energy disruption to get a market share from utilities | Low short-term return on investment for cash-constraint players |

### 1.1.4 New Energy Solutions

Digitalization is changing our energy systems. New and digital energy solutions, such as Smart Homes, Advanced Energy Monitoring Systems, and Visualization systems using Artificial Intelligence and Virtual Reality, are changing the perspective of future energy systems.

**Table 5 SWOT Analysis for New Energy Solutions**

| | Strength | Weakness | Opportunity | Threat |
|---|---|---|---|---|
| Utilities | Access to end-consumers data | Lack of innovation ecosystem | Potential new opportunities | Expose to competition and change of regulation |
| Large Energy Consumers | Asset and data ownership | Lack of knowledge and experiences | Cost saving | Cyber-security threats |
| New Players | Organizational agility and innovation thinking | No access to data | New business opportunity and blue ocean | Pave the way for big players |

Digitalization is much more advanced in other sectors in comparison with energy sector. The technology is advanced and ready to be used. However, cost-effective business cases are not available. All the above groups can pay their share to define such business cases. Utilities have access to all historic data and have the past knowledge of energy systems. Large Energy Consumers know their needs and the vision on how to save energy and optimize energy consumption [20]. Finally, the New Players bring the energy and enthusiasm to drive change and make New Energy solutions a reality. In this thesis, Sustainable Transportation and Local Energy System are being discussed and addressed.

## 1.2 Model for Electrification of Transportation (MET)

The state of the art of this thesis is that modelling the path in electrification of transportation from policy to electricity market and finally to charging poles are studied as shown in Figure 6.

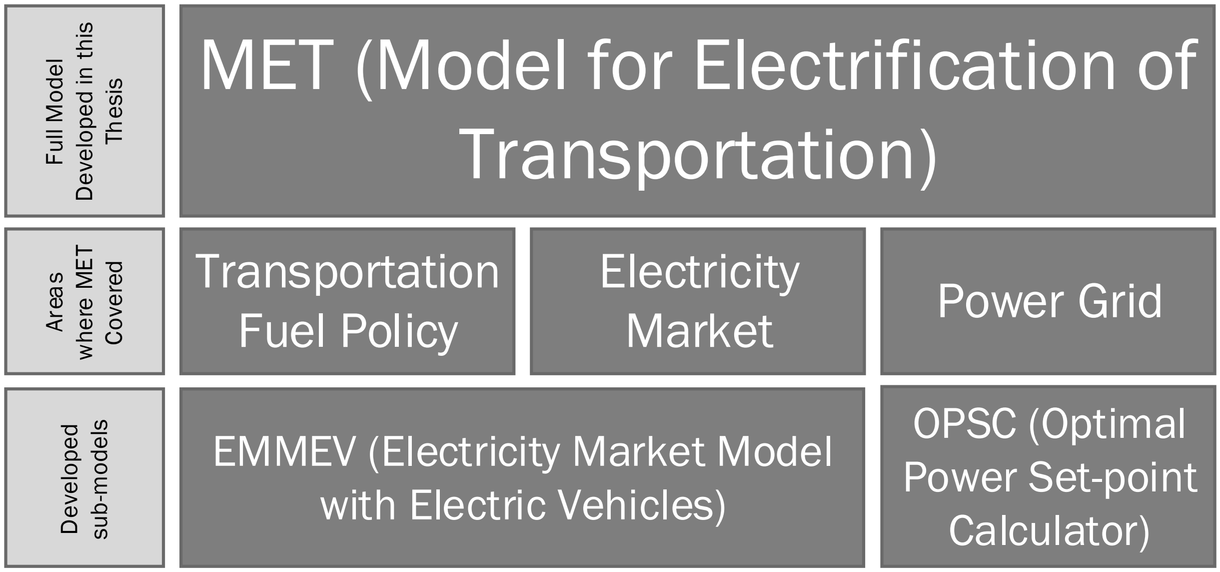


**Figure 6 Full path in electrification of transportation studied in this thesis**

The first step in electrification of transportation is to introduce relevant fuel policy to support the low-carbon transportation. Model for Electrification of Transportation (MET) has the flexibility to get different policies as input. In this thesis, Low Carbon Fuel Standard (LCFS) is selected and modelled.

The second step is to model how the increased number of EVs is managed in the electricity market and how this can affect the electricity price and revenue of those entities managing the EVs (EV aggregators). In this thesis, the Energy Service Company (ESCo) can make profit by offering EV aggregation services. The two main streams of revenue for ESCo through EV aggregation services are from the *electricity market* and *Low-carbon Fuel Standard (LCFS)*. In the electricity market, ESCo can earn money by contributing in day a head market, power regulation or automatic reserve. However, in this thesis, the day-ahead market is considered and modelled. On the other hand, ESCo can gain from their EV aggregation services and LCFS. This part of the path toward electrification of transportation is modelled in Electricity Market Model with Electric Vehicles (EMMEV).

Finally, the increased number of EVs needs to be charged by means of charging poles in the power grid. In this thesis, the management of the load from electric vehicles in a Micro Grid structure is introduced. The Optimal Power Set-points Calculator (OPSC) is introduced to calculate the power set-point of each charging pole at each hour based on the power systems constraints.

## 1.3 Research questions

Sustainable transportation and electrification of transportation are very much interrelated [21]. It is hard to imagine reducing emissions in transportation by ignoring the role of electrified transportation. A Life Cycle Analysis is needed to know exactly how electrification can reduce emissions in transport and make a local decision for promotion alternative fuels. However, in most cases, electricity can make significant contribution [22]. Therefore, sustainable transportation programs in different countries almost always involve e-mobility programs. EVs have high potential of taking a large share of future vehicle sales, as described in [4] and in Figure 3. As discussed above, researchers around the world have been performing a wide and promising range of studies on the availability of the grid for large-scale integration of EVs and the incentive analysis for EVs [8].

E-mobility programs include policy drivers in order to encourage the vehicle buyer to pay the higher price of Electric Vehicles (EVs) and promote installation of charging infrastructure [23] [24]. These will eventually increase the number of EVs and raise electricity consumption [8] [25] and will impact on the electricity market as a single platform for the electricity trade.

One of the regulatory measures for increasing the share of low carbon fuels is called Low Carbon Fuel Standard (LCFS) [26]. A LCFS regulates the carbon content of different fuels in transportation in order to reduce the emissions. It is quantitative and performance-based policy driver which tends to decrease Carbon Intensity (CI) in transportation fuels. This has been implemented in California and is being discussed to be implemented in other places [27] [26]. More details will be provided on the State of the Art.

EMMEV is a platform for testing different policy drivers with a view to increasing the number of Electric Vehicles and charging infrastructure on the electricity market. In this thesis LCFS is used as a policy to be tested. The area which EMMEV targets is the intersection of the electricity market with low-carbon transportation support policies. Throughout this thesis, the mutual effects of LCFS and the electricity market are described and discussed. The research questions are as follows:

1. How does LCFS policy increase the number of EVs?
2. How does the increased number of EVs influence the price of electricity?

3. What are the factors, including the ones from the electricity market, which make LCFS a more effective policy?
4. How do the technical constraints on a power system influence the charging of EVs?

These questions are addressed and discussed throughout this thesis.

## 1.4 Objectives

In [28], three phases of introduction of EVs are defined: catalyst, consolidation and advanced. Catalyst phase refers to the existing situation of introducing EVs when there are few EVs in cities and policies mainly target the uptake of EVs. In the consolidation phase, a larger number of EVs are introduced in the cities and the major policy target areas are EV management. This includes adapting the design of the energy market and studying the design of Time of Use (ToU) kind of tariffs. Finally, the advanced phase targets a full integration of EVs and adjustments such as a harmonization of the market.


**Figure 7: Three phases of introduction of EVs**

In the consolidation phase of EV development, when the results of this thesis are useful, the main objectives of this thesis are defined as follows:

1. Developing a model of electricity market with EVs in Agent-Based Modeling (ABM) platforms
2. Investigating what type of business models are both more profitable for ESCo business owners and will promote dissemination of EVs
3. Defining electricity market rules to ease the progress of EVs' development to the advanced phase with large amount of EVs proliferating in the cities
4. Investigating Electric Vehicles in a Micro Grid structure.

The objectives and the research questions are mapped to each other as shown in the

**Table 6: Mapping of research question to the objectives of this thesis**

| No. | Research question | Related objective |
|---|---|---|
| 1 | How does LCFS policy increase the number of EVs? | 1, 2, 3 |
| 2 | How does the increased number of EVs influence electricity price? | 1, 2, 3 |
| 3 | What are the factors, including the ones from the electricity market, which make LCFS more effective policy? | 1, 3 |
| 4 | How do the technical constraints on a power system influence the charging of EVs? | 4 |

This thesis intends to investigate, in the complex environment of the electricity market, the needs for new regulation as well as business opportunities for ESCos. In addition, from the grid side, the charging of EVs in Micro Grid is investigated.

## 1.5 Organization of the thesis

This thesis is structured around Model for Electrification of Transportation (MET) with its three main topics:

1. Fuel Policy
2. Electricity Market
3. Power Grid

The thesis is organized in 7 chapters as follows:

Chapter 1. Introduction
Chapter 2. State of the Art
Chapter 3. EMMEV: An Agent-Based Model
Chapter 4. Test System for EMMEV
Chapter 5. EMMEV Results and Discussions
Chapter 6. Optimal Management of Battery Charging of Electric Vehicles with Micro Grids
Chapter 7. Conclusions and Future work

Table 7 shows the organization of the thesis in each chapter, the related topic in each chapter.

**Table 7 Organization of the thesis**

| Chapter number | Title | Related Topic |
|---|---|---|

| | | |
|---|---|---|
| 1 | Introduction | 1, 2, 3 |
| 2 | State of the Art | 1, 2, 3 |
| 3 | EMMEV: An Agent-Based Model | 1, 2 |
| 4 | Test System for EMMEV | 1, 2 |
| 5 | EMMEV Results and Discussions | 1, 2 |
| 6 | Optimal Management of Battery Charging of Electric Vehicles with Micro Grids | 3 |
| 7 | Conclusions and future work | 1, 2, 3 |

The thesis starts with an introduction, Chapter 1, then, in Chapter 2, State of the Art is described. Electricity Market Model with EVs (EMMEV) is described in detail in Chapter 3. In these chapters, the author describes his perspective on modeling and Agent-Based Modeling. In addition, classes and general structure of the EMMEV are described. Two legs of EMMEV (day-ahead electricity market and Low Carbon Fuel Standard) are described.

In chapter 4, the test system, which is being used to test EMMEV as whole, is described. In chapter 5, results from EMMEV are presented. This included the interactions between two legs of EMMEV.

Chapter 6 discusses more charging strategy of EVs in Micro Grid environment. A separate test system and some results from Optimal Power Set-point Calculator (OPSC) are outlined in this chapter.

Finally, in Chapter 7, the thesis contribution in the science developments in this field are described and future works from this thesis are proposed.

# Chapter 2
# State of the Art

This thesis investigates and models the charging of Electric Vehicles from upstream related to support scheme and electricity trade in the electricity market to downstream related to charging infrastructure and strategies. This has been shown in Figure 6. The state of the art of this thesis is that the full path in electrification of transportation from policy to electricity market and finally to charging poles are studied.

The management of Electric Vehicles charging in the structure of the electricity market is addressed by an Agent-Based model called Electricity Market Model with EVs (EMMEV). The number of EVs is set by a transportation support scheme. The support scheme chosen for this thesis is called Low Carbon Fuel Standard (LCFS). LCFS is a support mechanism for increasing the share of low carbon vehicles. This is a market-based mechanism, and the market regulator sets long-term targets for the share of low carbon vehicles. EMMEV considers only participation of EVs in the day-ahead market. In the day-ahead market, the price of electricity is set. Therefore, the extra load from EVs can affect the price of electricity. All the models consider perfect competition market environment.

Charging infrastructures and EV charging strategies are investigated in Micro Grid structure. Since EVs will partly get their required energy from the power grid, they are considered as a new type of load with considerable charging requirements, and therefore the technical impacts of progressive integration of EVs in system operation have to be evaluated based on planned scenarios, especially for distribution networks. In addition, further scenarios characterized by increasing penetration levels of renewable power sources with intermittent nature, such as wind and photovoltaic generation, and also microgeneration systems connected to Low Voltage (LV) distribution grids should be taken into account.

## 2.1 Model for Electrification of Transportation (MET)

Figure 8 shows the areas which MET covered and will be described in details in this section of the thesis.

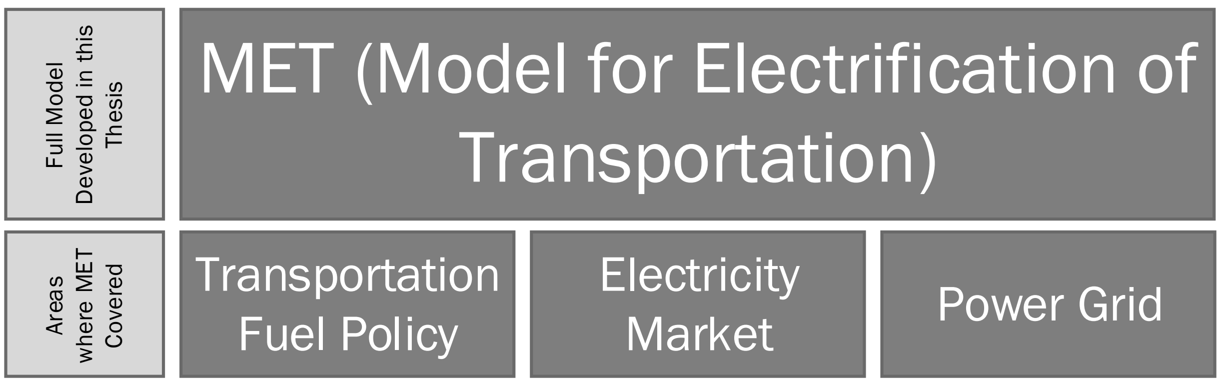


**Figure 8 Areas covered in Model for Electrification of Transportation (MET)**

As shown in Figure 8, Electrification of Transportation is a process that several elements needs to aligned. First, there has to be a proper fuel policy to motivate people to transform their vehicle to electric. This is mainly financial incentives due to higher cost of EVs. Electricity market needs to have proper processes to accommodate Electric Vehicles. Finally, power grid needs to be ready and has enough capacity to accommodate the charging of EVs. In this section of the thesis, the state of the art for this thesis which is the model for the full path toward electrification of transportation is described.

### 2.1.1 Transportation Fuel Policy

The transition to low-carbon transportation fuels is becoming more important and needs a fast change [29]. However, introduction of low carbon fuels in transportation is hindered by many limitations and problems. These include reduced investments and barriers in technology development and energy industries, other forms of technological and market inertia delaying investments in deployment and R&D, cartel pricing, and the failure of markets to assign a price to greenhouse gas (GHG) emissions [26].

Various policies are adopted to overcome these market failures and barriers, ranging from regulatory measures, such as emission regulations and fuel economy standards, to financial levers such as tax reductions, rebate and feebate [30] schemes. There are other drivers such as waivers for parking places and tolls and specifying separate driving lanes for EV drivers. Each has different advantages and disadvantages [24].

Among the regulatory measures, LCFS is a quantitative and performance-based policy to reduce GHG emissions in transport. An LCFS is a policy designed to accelerate the transition to low-carbon alternative transportation fuels by stimulating innovation and investment in new fuels and technologies. The goal is to provide a durable policy framework that will stimulate innovation and technological development. Since 2007, an LCFS policy has been adopted by California, the European Union (Fuel Quality Directive, FQD), and British Columbia (Renewable and Low-Carbon Fuel Requirement Regulation, RLCFRR) [31] [32] [33].

The design of an LCFS is premised on the use of technology-neutral performance targets and credit trading, with the intent of harnessing market forces and providing industry with flexibility. It is also premised on the use of life-cycle measurements of GHG emissions, to ensure that emissions are regulated effectively and scientifically. An LCFS is a hybrid of a regulatory and market policy instrument. It does not include mandates for any particular fuel or technology and as such does not attempt to pick winners or losers. Instead, it defines an average emissions intensity standard—measured in grams $CO_2$ equivalent per mega-joule of fuel energy ($gCO_2e/MJ$)—that all energy providers must achieve across all fuels they provide. Many options exist for meeting the standard. Regulated parties are free to employ any combination of strategies that suits their particular circumstances and perspectives—including the purchase of credits from other companies.

There is similar market to LCFS but in renewable electricity generation sector which is called Renewables Certificate Market (RCM). RCM was first started in 2002 by RPS (Renewable Portfolio Standard) [34] and it was also implemented in 2003 in Sweden, where it was called *elcertifikat*. Norway joined Sweden in 2012 and they created Nordic *elcertifikat* market [35]. The main goal of this market is to promote electricity generation from renewable resources [36] [37]. This market has been compared with LCFS in Table 8.

**Table 8: Comparison of LCFS and Renewables Certificate Market**

| Market | Main goal | Players | Certificate receivers | Quota obligation |
|---|---|---|---|---|
| RCM | Promote renewable electricity generation | Electricity generation units and large electricity consumers and electricity retailers | 1 certificate for each MWh of electricity generated from renewable resources | 1 quota obligation for some percentage of electricity consumption |
| LCFS | Promote carbon free transportation | Energy providers for transportation | 1 credit for CI reduction | 1 credit for sales of fuel with higher CI than LCFS |

Both LCFS and RCM aim to reduce GHG emissions. The target of RCM is the electricity generation sector while LCFS aims to reduce GHG emissions in the transportation sector. The players in RCM are generation units and the electricity consumers. However, in LCFS, the players are energy providers in the transportation sector.

In RCM, each player can receive one certificate for each MJ of electricity generated from renewable resources. Electricity consumers are obliged to buy certificates based on the amount of electricity they consume. In LCFS, each player may receive a credit/deficit for each equivalent MJ of energy sold to the end user. LCFS defines an average emissions intensity standard that all energy providers must achieve across all fuels they provide.

#### 2.1.1.1 Operation of Low Carbon Fuel Standard

LCFS is a policy instrument enabler to promote carbon-free transportation. In a perfect competition environment, it is expected in LCFS that fuels with lower Carbon Intensity (CI) will naturally get the higher share of the market. The goal is to introduce a quantity-based carbon-free fuel promotion in the transportation sector in order to reach a target for GHG emissions. In California LCF, the target is 10% reduction in overall Carbon Intensity by 2020 [38].

Mobility Credit (MC) is credit which LCFS issue to the market players for their low-carbon fuel distribution. There are some players in the market who are obliged to buy Mobility Credits (MCs) from those who are eligible to receive MCs from regulators. [39] [40]. The lower the CI of supplied fuel, the higher the chance of each specific player receiving credit (positive credit) and the higher the CI of a fuel, the higher the chance of each specific player being obliged to receive deficit (negative) credits.

All companies which provide fuel to the end users in the transportation sector are the market players. They are indirectly mandated to reduce GHG emissions by reforming the fuel supply. Considering three groups of fuel alternatives in transportation, gas (all type of conventional fuels and biofuels), hydrogen and electricity, the players are as follows:

- Biofuel producers and distributors
- Gasoline producers and distributors
- EV station owners.

It is true that most of the time biofuel and gasoline have the same stations, but it is assumed that the credit goes to the different sections of the same distributor for different fuel types. The revenue from MCs needs to be distributed among the energy providers and car drivers to both support the installation of infrastructure and cover the higher price of carbon-free vehicles.

#### 2.1.1.2 Electricity in LCFS

In California, LCFS have been introduced since 2009 to reduce Carbon Intensity (CI) by 10% until 2020 [40]. On September 25, 2015, the LCFS Board in California approved the re-adoption of the LCFS. Under the new regulations, new players are introduced in the market in which electricity used as a transportation fuel can generate MCs. These players are Electric Vehicle Service Providers (EVSP) for public charging, Electric Vehicle (EV) fleet operators, battery switch station owners, site hosts of private access EV charging equipment at a business or workplace, transit agencies operating a fixed guide system or electric buses and the Electrical Distribution System Operators (DSO) for residential charging, and for all of the above categories. These, in general, are the ESCo which are in charge of EVs [41].

Several lower-carbon fuels, as they meet the CI targets in 2020, will be exempted from LCFS. The entities which are providers of those fuels have no obligations for these fuels under LCFS, in case they decide not to join in the LCFS program. However, if they decide to participate in LCFS, they can gain MCs and trade it in the structure of LCFS [41].

#### 2.1.1.3 Trading in LCFS

At the end of a compliance period (one year for most LCFS programs), a player that owns credits and also has incurred deficits must 'retire' a sufficient number of credits to meet the obligation for that compliance period. The regulator normally sets a maximum price at the beginning of each year ($200 for California) [40]. The players in the LCFS can trade in their MCs in one of the following markets:

- Ongoing LCFS Credit Market
- Credit Clearance Market.

The ongoing LCFS is like a bilateral contract in which at any time during their compliance period, the players can trade their credits with a bilateral contract. This is very much similar to forward contract in the electricity market [42]. The risk in those contracts are generally lower.

The players must acquire credits pledged into the Credit Clearance Market to be retired toward compliance in the previous compliance year. Credits acquired for this purpose are defined as "Clearance Market" credits [40].

MC are calculated based on a CI defined by regulators for each year. This number is expressed in $gCO_2E/MJ$. All the players are evaluated based on this number in order to be eligible to get MC (have credit) or obliged to buy MC (have deficit). In California in 2015, the LCFS was readopted and the CI modeling updated. The average carbon intensity requirements for years 2016 to 2020 reflect reductions from revised base year (2010). The maximum pass through LCFS for 2016 is *99.7* $gCO_2E/MJ$.

In order to calculate MC, the following steps should be followed [39]. First, the energy (MJ) for the sold energy in transportation by each player is calculated. The conversion factors from liter (in case of liquid fuels) or kWh (in case of electricity fuel) are available by regulators.

As the second step, the Energy Economy Ratio (EER) is considered. EER aims to account for differences in energy efficiency for vehicles and adjusts to take these differences into account. EER for gasoline is 1 (meaning that it doesn't make a difference), but it is 3 for electricity (meaning each MJ of electricity is three times more efficient than gasoline).

The third step is to calculate the difference between the LCFS and the CI of the fuel sold. If LCFS is lower than CI of the fuel sold, the player is producing deficit and is obliged to buy MC (get deficit). In case of higher LCFS than the due amount sold, the player is eligible to receive MC (get credit).

The fourth and last step is to convert the credit/deficit into grams of $CO_2$ equivalent. Credit/deficit are expressed in greenhouse gas emissions volumes, where credits indicate the emissions "saved" by selling a low carbon fuel compared to selling a fuel that exactly meets the low carbon fuel standard for that year. The final number shows the number of deficit/credit that each player will get for the fuel sold each year.

### 2.1.2 Electricity market

The role of EV aggregator is defined and analyzed in different literature including [43] [44] [45] [46]. An aggregator is an enabler of the EV integration in the electricity market and power system operation. Power system operators see the EV aggregator as part of a hierarchical control architecture, which coordinates the EV charging in response to the system operators' signals. EV owners see the aggregator use their available flexibility to purchase electrical energy at a low price and sell ancillary services in the electricity markets, which ultimately lead to a retailing tariff reduction [47]. The aggregators are under the framework of the control structure in the power system and this has been shown in Figure 9 [48].

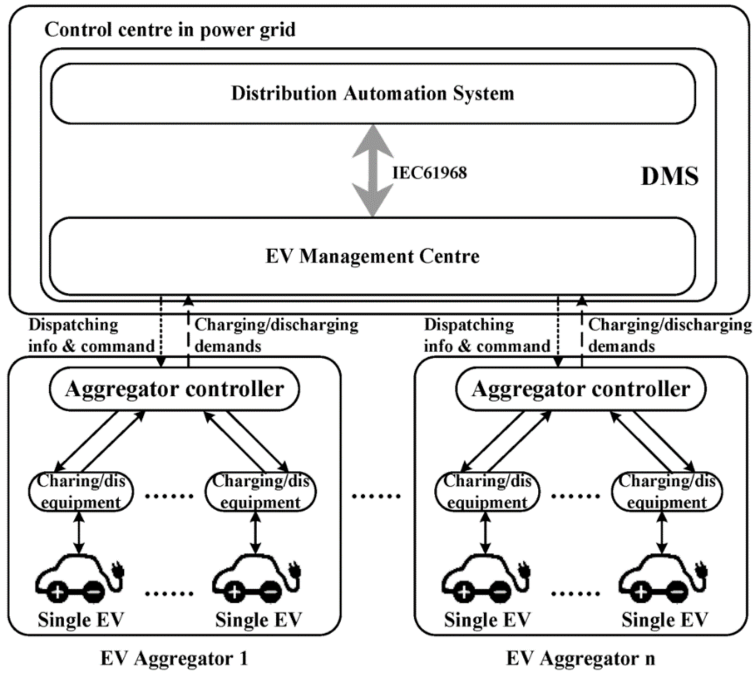


**Figure 9: Aggregator under the framework of the control structure [48]**

EV aggregators are a middle entity between the Distribution System Operator and the EV drivers to manage and control the load from the EVs. The EV Management Center manages the aggregators in connection to Distribution System Operators.

#### 2.1.2.1 EVs in the future electricity markets

Electric Vehicles (EVs) load is sufficiently considerable that they can participate in the day-ahead market. However, due to their flexibility, they can participate in power regulation or automatic reserve. Therefore, EVs can participate in the electricity market in the following modes [49]:

1. Day-ahead market
2. Power regulation market
3. Automatic reserve

#### 2.1.2.2 EVs in day-ahead market

This is the most straight-forward market where EVs can contribute. Load Balance Responsible (LBR) is an entity in the electricity market which is responsible to balance the demand and supply of power. LBR will send the bids from EVs to the market. There, different models with or without EV aggregator contribution are defined by different authors such as [50]. In the case without aggregator, the load from EVs is considered as normal load and it is traded in Electricity Market. In case of EV aggregator, the load from EVs is aggregated and separate entity trade the relevant load in the electricity market.

#### 2.1.2.3 EVs for power regulation

The existing additional requirement of real-time measurement is problematic and will either have to be relaxed or addressed in case EVs are to gain access to the regulating power market. If the requirement is relaxed for smaller units, concepts such as Flex-Power [50] will become viable. If the bid requirement is also relaxed, a 'self-regulating' concept will become relevant, as it places the responsibility for anticipating the demand response in the hands of the transmission system operator (TSO) and, thus, does not require the retailers to send bids for delivering regulating power. As is the case with EV participation in the day-ahead market, congestion in the distribution grid also requires a fleet operator and/or new various market tools.

#### 2.1.2.4 EVs as automatic reserve

If EV owners are willing to participate in the market for automatic reserves, they will either have to enter into an agreement where they receive compensation in return for allowing their vehicle to stop charging when the frequency drops, or enter into an agreement with a fleet operator who will be able to provide automatic reserves by pooling EV users. In the first concept, a device that automatically cuts out when the frequency drops below a predetermined set point is required. The fleet operator concept, meanwhile, requires a technology to allow for the fleet operator to control the charging of the vehicles, and in this regard could provide frequency control in either direction [50]. This is called local and dedicated EV load-shedding mechanism [51]. In other words, part of the load can be shed locally in case of low frequency for specific number of EVs.

### 2.1.3 Power Grid

Different authors analyzed the technical feasibility of large scale introduction of EVs independent of economic and policy issues [52] [53] [10] [9] [54]. These studies made scenarios for driving of EVs and future load pattern from EV charging. The results showed that the existing grid infrastructures can handle a large percentage of existing conventional cars converted to EVs in case smart charging pattern is implemented. However, residential areas are subject to more problems from grid infrastructures capacity perspective in case one-phase charging facility is the only available one. These studies reveal that the power grid has a large enough capacity to accommodate a high number of EVs by implementing smart charging strategies.

EVs, due to their low driving cost and the ubiquitous availability of electricity, have a higher chance to replace conventional vehicles compared to, for example, fuel cell vehicles. Supporting the last statement, R. Fazeli and V. Leal developed a multi-criteria decision-making problem for the fuel alternatives in transportation [22]. Based on the different attributes including emissions, vehicle costs and availability of the fuel, EVs are among the top-ranked alternatives. Bandivadekar [55] performed similar studies on the impact of different fuel alternatives in US light-duty vehicles, and the results indicate a dominant position for EVs in the future share of vehicles. In addition, a life cycle analysis of three important alternatives for the future of the transportation sector (internal combustion engine, fuel cell and EVs) shows that EVs have relatively much lower life cycle costs [56]. Therefore, it seems to be fair to assume that with the increase of EVs, significant emission reduction is achievable (This is only possible if renewable generations units are the majority in the electrical energy portfolio of generation).

By increasing integration of renewable resources to the distribution grid, it is expected that the grid is operated by exploiting Micro Grids concept. Micro Grid is a localized grouping of electricity generation, energy storage, and loads that normally operate connected to a traditional centralized grid. This makes it possible to manage the integrated EVs by means of the controllers defined for this purpose [57]. In the hierarchy control scheme of a Micro Grid, there are both local controllers and a head controller (Micro Grid Central Controller) who maintain control both locally in each low voltage bus bar and globally in the medium voltage bus bar. The control variable for smart management of EVs is the power set-points of each EV. A new feature is embedded in the Micro Grid Central Controller (MGCC) which calculates the power set-points of EVs integrated to the Micro Grid. This feature is called Optimal Power Set-points Calculator (OPSC) which is described in [58].

The implementation of a smart management system where the EVs are supposed to be connected to active LV networks with microgeneration units, involves dealing with the Micro Grid (MG) concept [9]. Thus, single phase electrical batteries belonging to EV are included on the MG through a smart power electronic interface with a specific control approach called the Vehicle Controller (VC). In charging mode, the VC will receive active power set-points from a Micro Grid Central

Controller (MGCC), housed at the MV/LV secondary substation level, to charge the EV batteries, considering the LV network operating conditions. A Micro Grid (MG) is a group of electricity generation units and loads in a certain location which can be operated both in connected mode to wide area synchronous grid or also in islanded mode.

## 2.2 Agent-Based Modeling

The Oxford American Dictionary define the word 'agent' as 'a person or thing that takes an active role or produces a specified effect'. Computer science researchers have used the word 'agent' for more than twenty-five years as 'an entity that performs a specific activity in an environment of which it is aware and that can respond to changes'[59].

The modeling tool in this thesis is Agent-Based Modeling (ABM) [60]. ABM is composed of several agents. The agents may have the inherent properties of flexible autonomy, re-activity, pro-activeness, social ability, the distributable nature of agents, the possibility of emergent behavior and the fault tolerance of the agent systems in a certain environment based on the dimension of the complexity defined above[61] [62].

Multi-Agent Systems (MAS) is the other term which is being used in some texts and which can lead to some confusion. Agent-Based Modeling (ABM) and Multi Agent System (MAS) refer to the same modeling way while ABM aspires to descriptive perception into the combined behavior of agents, while the goal of MAS is to procure agents or solve specific practical or engineering problems [63].

### 2.2.1 Agent-Based Modeling Tool

There are several tools available in order to model a system with agents. Among those, Repast are chosen for this thesis. These tools are compared in the following table.

The MAS modeling platforms which will be used to develop a preliminary model is called NetLogo [64]. NetLogo is also an agent-based programming language and integrated modeling environment. The programming language is inspired by Logo programming language and the program is easy to understand.

**Table 9: Comparison between NetLogo and Repast**

| | NetLogo | Repast |
|---|---|---|

| | | |
|---|---|---|
| Developed by | Northwestern University | Repast Organization for Architecture and Development |
| Advantages | Very easy to set up and run models | Many users, good support from the Repast community |
| Example models | Many | Many |
| Disadvantages | Very complicated models are outside the capability of NetLogo | Need to be able to understand a programming language (Java) |
| Time required to start building models for programming beginner | Short | Longer |
| Limitations | Models created cannot be easily extended. | Very versatile system. Models can be extended very easily. |
| Support from academic community | High | High, especially from social sciences academic community. |
| Active maintenance of software | High | High |
| Additional features | 3D visualization of models. Capability webpage usage | GIS implementation |

Repast (Recursive Porous Agent Simulation Toolkit) [65] is a free and open-source agent-based modeling and simulation toolkit. Repast has multiple implementations in Java and includes built-in adaptive features, such as genetic algorithms and regression. Java programming language toolkit of Repast is selected to perform the advanced modeling of this thesis. The Repast system is a Java-based middleware for the development of trivial agent platform and agent models. It was developed at the University of Chicago's Social Science Research Computing division and is derived from the Swarm simulation toolkit. Repast offers a set of reusable Java Bean components, along with several flexible interconnection methods to combine those components and thus create software agents. Furthermore, Repast uses the base of the Knowledge Query and Manipulation Language (KQML) to promote communications among agents inside the platform. KQML provides the bases for the most widely-used agent communication language (ACL), and over the last few years it has been extended, modified and standardized by Foundation Intelligent Physical Agents (FIPA) [66], using KQML to send performatives to indicate the action that another agent should take on its behalf. Another major meaning of the KQML is the use of ontologies to ensure that two agents communicating in the same language can correctly interpret statements in that language. The main reason for the choice of Repast is Java Bean technology, which allows new computational features to developers to reap the benefits of rapid application development in Java by assembling predefined software components.

## 2.3 Summary and Discussion

In this section of the thesis, the State of the Art which is full path of electrification of transportation is described. The model is called MET and it has three main areas:

1. Transportation Fuel Policy
2. Electricity Market
3. Power Grid

As discussed in this section, in various other researches, the effects of EVs in the power grid and electricity market separately. There is a gap on addressing the whole chain from the low-carbon transportation policy (in this thesis LCFS) which leads to higher number of EVs and then down to electricity market effects of EVs. This is the gap which has been identified and the models in thesis (EMMEV) is developed to investigate this gap in more details.

On the low-voltage level, there is research gap of addressing EV charging with Smart Charging strategy and a right structure with local utilization of renewable generation at the Microgrid level. This part of thesis research is done at INESC Porto. A Micro Grid structure to control different load and micro generation units is introduced. In addition, in this thesis, a smart charging strategy is used to make best use of the power system infrastructure and maximizing the use of local micro generation while charging EVs.

This thesis has a multi-disciplinary nature to address the interconnection between policy for transportation and electricity market (EMMEV). In addition, an element of technical power systems related to EV charging, as downstream issue is addressed and discussed in this thesis.

# Chapter 3
# EMMEV: An Agent-Based Model

Electricity Market Model with EVs (EMMEV) is being developed considering both contributions of EV aggregators in the electricity market and in LCFS. In this chapter of the thesis, the details of this model are described.

In [67], a survey of the most relevant publications regarding the electricity market modeling is presented. Very few of those addressed the joint effect from transportation policy down to the electricity market. EMMEV is a simulation model to investigate the behavior of agents in the joint environment of the transportation sector and the electricity market.

## 3.1 Basic concept and definition

Following the same concept used in electricity markets, the proposed application is called EMMEV, and consists of two sections: the electricity market and Low Carbon Fuel Standard. There are two layers in the model: the agent layer, which is the core of the modeling, and a geographical layer, which addresses different geographical locations for different case studies. EMMEV studies the interactions of agents between 2016 and 2030. Regardless of all the number of languages, frameworks, developed environments and platforms published during the last decade in the literature, implementing MAS is still a complex task, which in general is coded by using middleware as Repast [65] described in State of the Art.

The reason why Agent-Based Modeling is used for EMMEV is that with ABM, the system is experimented and the mathematics (by numbers and formulas) of the system will be analyzed. This is highly appreciated in a complex system like the electricity market where several agents are present and can behave in a very complex way. ABM models the behavior of ESCOs according to economic reasoning to maximize the profit.

ABM is considering both experimental and mathematical styles of thinking. Simulations in ABM are like real-world experiments (but controlled and simplified) so that's why an agent-based modeler must think like an experimentalist. In the structure of electricity market, since the electricity price changes every hour and there is high need to experiment 24 hours a day, so ABM is preferred. The initial arrangement of agents, the structure of the environment, and what manipulations will be performed on the agents should be specified and controlled. The modeler must also determine what data are collected and how they are analyzed.

The mathematical style of thinking essential for ABM and for EMMEV also focuses on characterizing the behavior of a model in parameter space. Analytical methods are not available for this type of analysis, so a brute-force[4] computational analysis is used by running sets of simulation experiments that systematically explore different points in parameter space. Quite often, it is not practical to methodically explore a whole parameter space.  In these cases, a subset of parameter space to explore or search parameter space for "good" solutions. In EMMEV, since the test system is not too big, brute-force computational analysis is not used.

## 3.2 Structure of EMMEV

In this thesis, two separate mathematical models are developed: one for day-ahead electricity market and one for Low Carbon Fuel Standard. This has been graphically depicted in.

[4] Brute-force search or exhaustive search, also known as generate and test, is a very general problem-solving technique and algorithmic paradigm that consists of systematically enumerating **all** possible candidates for the solution and checking whether each candidate satisfies the problem's statement.

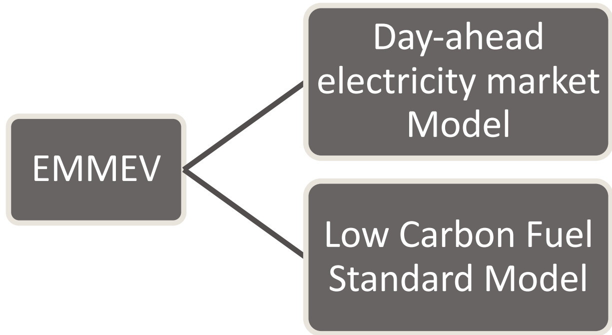


**Figure 10: EMMEV structure**

There are two layers in the model: the agent layer (which is the core of the modeling) and the geographical layer (which addresses different geographical locations).

ESCos will be modeled as Agents within the framework of ABM approach, of which there are profit-maximizing entities. Geographically, in this research there is a single electricity market in the model which consists of two countries. Each of the countries consist of two regions in which the price of electricity varies due to congestion in the lines between different areas. Based on the defined layers, there are six main classes defined in EMMEV. This is illustrated in the following .

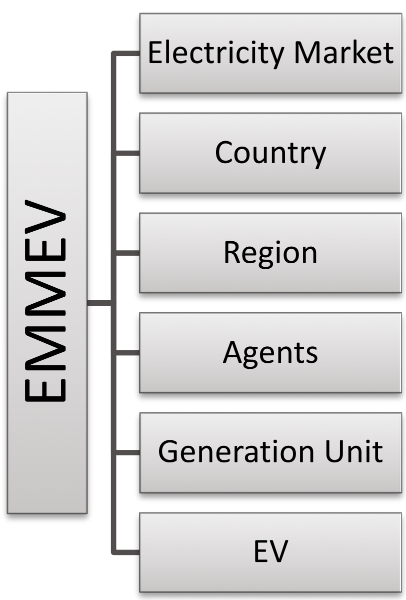


**Figure 11: Classes in EMMEV**

There is a hierarchy of classes from *ElectricityMarket* to *Country* and eventually to *Region.* This means that *Region* is a generalization of *Country*, and *Country* is a generalization of *ElectricityMarket* class. In each Region, numbers of Agents are located. *Agents* are ESCos. *ElectricityMarket* class is the main class in EMMEV concept. All the market rules are defined in this class. Unified Modeling Language (UML) is used to present each class, and the classes will be described in more details in the next sections of this thesis.

The agents are Energy Service Companies (ESCos) and it is assumed that the ESCos in EMMEV can provide at least one of the following services:

- Power generation
- Electricity retailing
- EV aggregation
- LCFS

In the structure of the electricity market, an EV aggregator can make revenue by providing services to the power grid. EV aggregator can provide solutions by contributing in spot market, power regulation market and automatic reserve. The price of each MWh of electricity sold to the power system operators for any of the preceding services varies. The simplest case is contribution of EV aggregator in spot market which is the main focus of the current phase of code development. The EV aggregator can benefit from each unit of electricity sold to EV drivers. EV aggregator can benefit from its contribution in Low Carbon Fuel Standard (LCFS) market [68] by getting the credits and then selling it at the right time. This benefit comes from selling Mobility Credits (MCs) in either Ongoing LCFS Credit Market or Credit Clearance Market.

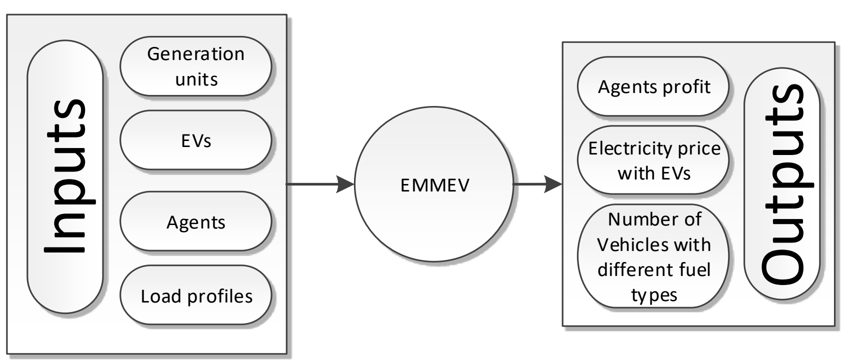


**Figure 12: The current structure of EMMEV**

As discussed above, agents can either own generation units or aggregate EVs and manage demand. It is important to mention that the agents cannot have both generation and retailing. The attribute related to either demand or generation should be always zero. This means that under unbundling of electricity market, the cost and revenue and the data from different Energy Services are fully separated in order to fully comply with unbundling regulation in all electricity markets around the world.

A list of existing generation units and EVs are the input to the EMMEV model. Each generation unit is owned and each EV is aggregated to one single agent. This is again in full compliance with the unbundling in the electricity market. All the agents have access to the same information, and cost and revenue for each Energy Service is fully independent from the other Energy Services (no market power). The Electricity price is also part of the output data for the model which will come from the market clearing procedure when the curve of offers intercepts the curve of demand. The market is asymmetrical where only the generation units can bid. This is the price at which the retailers buy their required electricity from the generation units. In this thesis, marginal market (depending on the marginal cost of the last generation to be dispatched to serve to all demand) is considered and no bilateral contracts are at the focus of modeling for the sake of simplicity. The bilateral contracts can be added to the model as an extension of the model.

On the other hand, retailers sell the electricity with different price patterns to EV drivers and households. These price patterns are also outputs to the model.

## 3.3 Agent-Based Modelling applied to the Electricity Market

In this section of the thesis, first UML is described and EMMEV is presented in class diagrams using UML in the following sections.

UML is a graphical language for visualizing, specifying, constructing and documenting the artifacts of a software-intensive system. UML provides a standard way to write system blueprints, covering conceptual ideas, such as business process and system functions as well as concrete items such as classes written in a specific programing language, database schemas and reusable software components [69]. UML has a vocabulary and like any other language, has building blocks. The UML building blocks are:

1. Things
2. Relationships
3. Diagrams.

These three will be defined in more details in the following sections of the thesis.

### 3.3.1 Things

Things are like abstractions. They are also treated as first-class citizens in a model. Relationships tie Things together and diagrams group interesting collection of things. There are four kinds of Things in UML:

1. Structural things
2. Behavioral things
3. Grouping things
4. Annotational things

Structural things are the nouns of UML models. These are the mostly static parts of a model, representing elements that are either conceptual or physical.

In all, there are seven kinds of structural things:

- Class
- Interface
- Collaboration
- Use case
- Active class
- Component
- Node

Definition of each type of conceptual thing is beyond the purpose of this thesis and the author refers the reader to [69] for further information. However, the most important and commonly-used structural thing is *class*. A class is a description of a set of objects that share the same attribute, operations, relationships and semantics. A class implements one or more interfaces and it is illustrated in Figure 13.

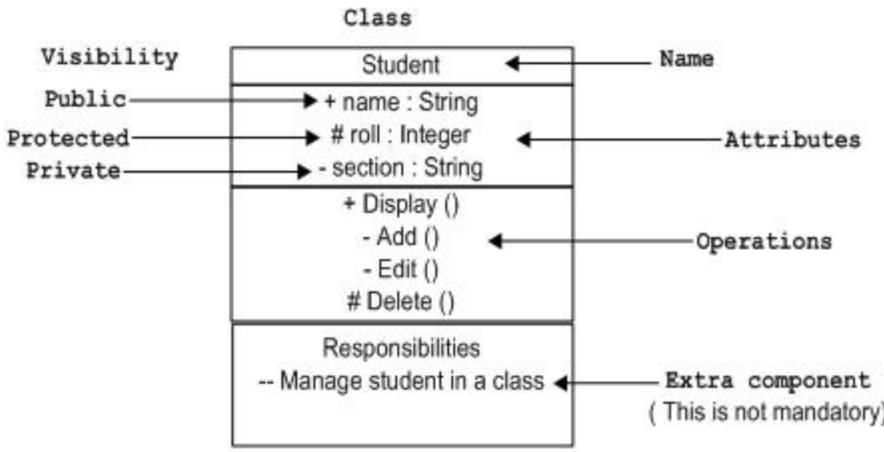


**Figure 13 Class representation in UML [70]**

An interface is a collection of operations that specify a service of a class or component. An interface therefore describes the externally visible behavior of that element. An interface might represent the complete behavior of a class or component or only a part of that behavior. An interface defines a set of operation specifications but never a set of operation implementations. Graphically, an interface is rendered as a circle together with its name as shown in Figure 14. An interface rarely stands alone.

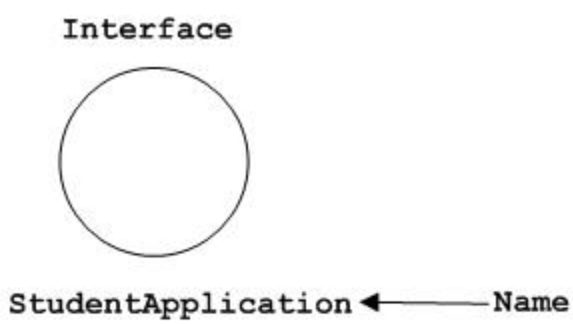


**Figure 14: Interface representation in UML [71]**

There are two types of behavioral things: interaction and state. The most commonly-used behavioral thing is interaction. Interaction is a behavior that compromises a set of messages exchanged among a set of objects within a particular context to accomplish a specific purpose. An interaction involves a number of other elements, including messages, action sequences (the behavior invoked by a message), and links (the connection between objects). Graphically, a message is rendered as a directed line, almost always including the name of its operation, as in

Figure 15. *State* in a state machine is a behavior that specifies the sequences of states an object or an interaction goes through during its lifetime in response to events, together with its responses to those events.


**Figure 15: Interaction representation in UML [71]**

These two elements, interactions and state machines, are the basic behavioral things that you may include in a UML model. Semantically, these elements are usually connected to various structural elements, primarily classes, collaborations and objects.

Grouping things are the organizational parts of UML models. These are the boxes into which a model can be decomposed. In all, there is one primary kind of grouping thing, namely, packages.

Annotational things are the explanatory parts of UML models. These are the comments you may apply to describe, illuminate and remark about any element in a model. There is one primary kind of annotational thing, called a note. For more information please refer to [69].

### 3.3.2 Relationships

There are four kinds of relationships in the UML:

1. Dependency
2. Association
3. Generalization
4. Realization.

These relationships are the basic relational building blocks of UML. You use them to write well-formed models.

First, a dependency is a semantic relationship between two things in which a change to one thing (the independent thing) may affect the semantics of the other thing (the dependent thing). Graphically, a dependency is rendered as a dashed line, possibly directed, and occasionally including a label, as in Figure 16.

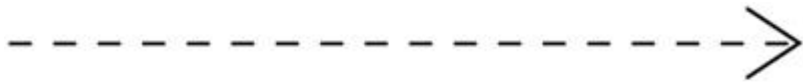

**Figure 16: Dependencies representation in UML**

Second, an association is a structural relationship that describes a set of links, a link being a connection among objects. Aggregation is a special kind of association, representing a structural relationship between a whole and its parts. Graphically, an association is rendered as a solid line, possibly directed, occasionally including a label, and often containing other adornments, such as multiplicity and role names, as in Figure 17.

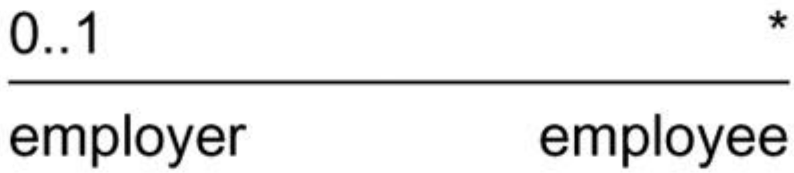


**Figure 17: Associations representation in UML**

Third, a generalization is a specialization/generalization relationship in which objects of the specialized element (the child) are substitutable for objects of the generalized element (the parent). In this way, the child shares the structure and the behavior of the parent. Graphically, a generalization relationship is rendered as a solid line with a hollow arrowhead pointing to the parent, as in Figure 18.

**Figure 18 Generalizations**

Fourth, a realization is a semantic relationship between classifiers, wherein one classifier specifies a contract that another classifier guarantees to carry out. You'll encounter realization relationships in two places: between interfaces and the classes or components that realize them, and between use cases and the collaborations that realize them. Graphically, a realization relationship is rendered as a cross between a generalization and a dependency relationship, as in Figure 19.

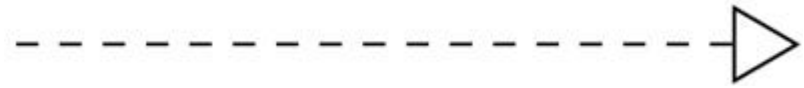

**Figure 19: Realization representation in UML**

These four elements are the basic relational things you may include in a UML model. There are also variations on these four, such as refinement, trace, include, and extend (for dependencies).

### 3.3.3 Diagrams

A diagram is the graphical presentation of a set of elements, most often rendered as a connected graph of vertices (things) and arcs (relationships). You draw diagrams to visualize a system from different perspectives, so a diagram is a projection into a system. For all but the most trivial systems, a diagram represents an elided view of the elements that make up a system. The same element may appear in all diagrams, only a few diagrams (the most common case), or in no diagrams at all (a very rare case). In theory, a diagram may contain any combination of things and relationships. In practice, however, a small number of common combinations arise, which are consistent with the five most useful views that comprise the architecture of a software-intensive system. For this reason, the UML includes nine such diagrams:

1. Class diagram
2. Object diagram
3. Use case diagram
4. Sequence diagram
5. Collaboration diagram
6. Statechart diagram
7. Activity diagram
8. Component diagram
9. Deployment diagram

Class diagrams are the most common diagram found in modelling object- oriented systems. A class diagram shows a set of classes, interfaces, and collaborations and their relationships. You use class diagrams to model the static design view of a system. For the most part, this involves modelling the vocabulary of the system, modelling collaborations, or modelling schemas. Class diagrams are also the foundation for a couple of related diagrams: component diagrams and deployment diagrams.

Class diagrams are important not only for visualizing, specifying, and documenting structural models, but also for constructing executable systems through forward and reverse engineering.

Developing more on the remaining diagrams is beyond the scope of this thesis and the author refers the reader to [69] for further information.

## 3.4 Agent-based modeling applied to electricity marker and Ontology Concept

Concepts which have been implemented in the EMMEV model are described in this section of the thesis. UML is used in order to describe the model in more details. In this section, first a general structure of the model (all defined classes) is described and then each class is described in detail and UML class diagrams are shown in Appendix 2.

Apart from the modules (called classes in this section) defined in section 3.6 of this thesis, there are four more classes defined in the model. So, there will be in total 8 classes defined in the model:

1. GenerationUnit
2. Agent
3. RunEMMEV
4. GlobalPlanner
5. Market
6. MarketOutput
7. BankingPlanner
8. ExcelHandler

Each of these classes is described in the next section.

### 3.4.1 GenerationUnit

Each generation unit in the model is an object of the class called *GenerationUnit*. The attributes of the generation units are shown in Figure 50. The attributes are all required specification from a renewable generation unit for our modeling purpose. Each agent manages part of the load in the market and serves the clients. It is important to mention that the agents cannot have both generation and retailing. The attribute related to either demand or generation should be always zero.

### 3.4.2 Agent

In EMMEV agents can provide different energy services. Therefore, the *Agent* class is defined to incorporate the preceding characteristics into the model. The UML class diagram of the *Entity* class is depicted in Figure 51 of Appendix 2 of this thesis.

The *generationUnits* in each *Entity* is a set of generation units which are owned by that specific entity. Entities can own any number of generation units. The quota obligation is presented by the percentage of the total consumption by each entity. The *shareOfMarket* determines the total consumption.

The *demand* is the other attribute for each agent. It is important to mention that the agents cannot have both generation and retailing. The attribute related to either demand or generation should be always zero.

There is one method implemented in this class: *calculateProfit*. This method calculates the profit for each agent for each year relevant to each entity.

### 3.4.3 RunEMMEV

The *RunEMMEV* class is the main class in the code. It is represented in UML as shown in Figure 52. *RunEMMEV* is responsible for putting methods, devised in other classes, in a sequence in order to run the model and calculates electricity price.

### 3.4.4 GlobalPlanner

*GlobalPlanner* is responsible for compiling quota obligation, creating entities and dealing with the change of year in time sequence of the model. The UML presentation is shown in Figure 53.

### 3.4.5 Market

The *Market* class is responsible for calculating certificate prices based on the supply curve of the certificates. The market class in UML is shown in Figure 54.

### 3.4.6 MarketOutput

The outputs of the market after each year is structured by the attributes of a class called *MarketOutput*. Market outputs have the following parameters. These parameters are also shown graphically in the UML class diagram in Figure 55 in Appendix 2.

### 3.4.7 BankingPlanner

Since the certificate receivers are legally free to bank their certificate, their decision on when to sell their certificate will largely affect the certificate price and the surplus of certificates shown in Figure 56.

### 3.4.8 ExcelHandler

*ExcelHandler* is a class responsible for interactions of EMMEV with Microsoft Excel files. The inputs are read from an Excel sheet and the results are sent to an Excel sheet by means of *ExcelHandler*. The *ExcelHandler* UML class diagram is depicted in Figure 57.

## 3.5 EMMEV in SGAM

In order to make it clearer which area EMMEV is addressing and specify modeling environment, SGAM (Smart Grid Architecture Model) is used. First, SGAM is described and them EMMEV in SGAM is depicted and explained.

### 3.5.1 About SGAM

The SGAM framework is intended to present the design of smart grid use cases in an architectural but solution- and technology-neutral manner [72]. The SGAM framework allows the validation of smart grid use cases and their support by standards. In SGAM, there are 5 layers, layers A–E, 5 domains, domains 1–5 and 6 zones, zones a–f. This has been shown graphically in Figure 20.

The Business Layer provides tactical and strategic goals, business processes and business services as well as regulatory aspects. There is no specific standardization on this layer.

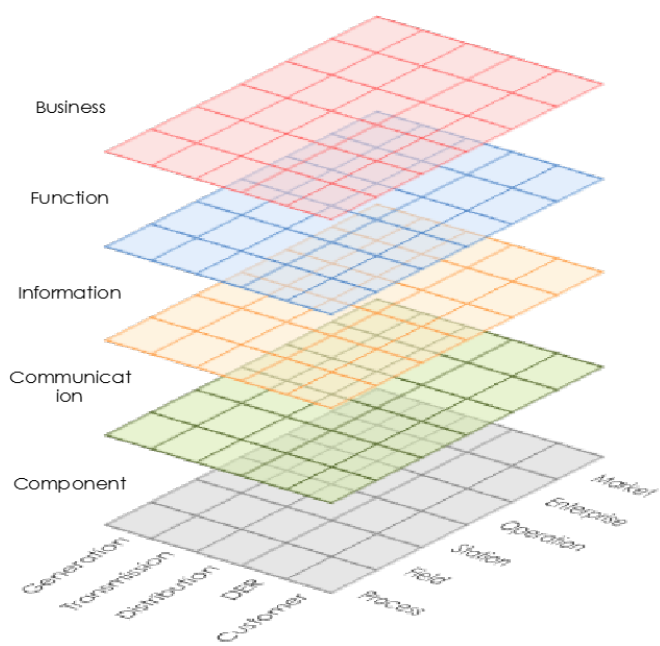


**Figure 20: Smart Grid Architecture Model**

The Function Layer discussed IT-oriented, technology-independent descriptions of general Smart Grid use cases, their functions and used technical services.

The Information Layer provides information about data and information models to support the exchange of business objects and data models of the Function Layer to enable interface interoperability.

The Communication Layer presents protocols and procedures for the data exchange between components based on the Information Layer.

The Component Layer provides a physical and technical view on Smart Grids components. Besides power system-related infrastructure and equipment, ICT infrastructure and ICT systems are also considered as possible items [72].

Each of the above-mentioned layers consists of five domains, each subdivided into six zones. Domains are established according to organizational cohesion to allow for simpler identification of organizational boundaries to identify inter-organizational interfaces. The domains are in particular made up from the supply chain in the energy sector in sequence, from generation to use. Accordingly, they are named Generation, Transmission, Distribution, DER and Customer Premises. The zones are defined according to zones of automation, i.e., from enterprise-level automation down to the process level. This is essential to distinguish between different types of technologies and standards used. The zones are named Market, Enterprise, Station, Operation, Field, and Process [72].

### 3.5.2 EMMEV in SGAM

In this section EMMEV is described in Smart Grid Architecture Model (SGAM) to bring clarity and to show on the high level where EMMEV is located. EMMEV addresses Business layer in Market and Enterprise Zone. Market Zone reflects the market operations possible along the energy conversion chain, e.g., energy trading, mass market, retail market. Enterprise zone includes commercial and organizational processes, services and infrastructures for enterprises (utilities, service providers, energy traders). These zones are connected to Charging Pole and Customer and Facility Domains. This has been shown graphically in Figure 21.

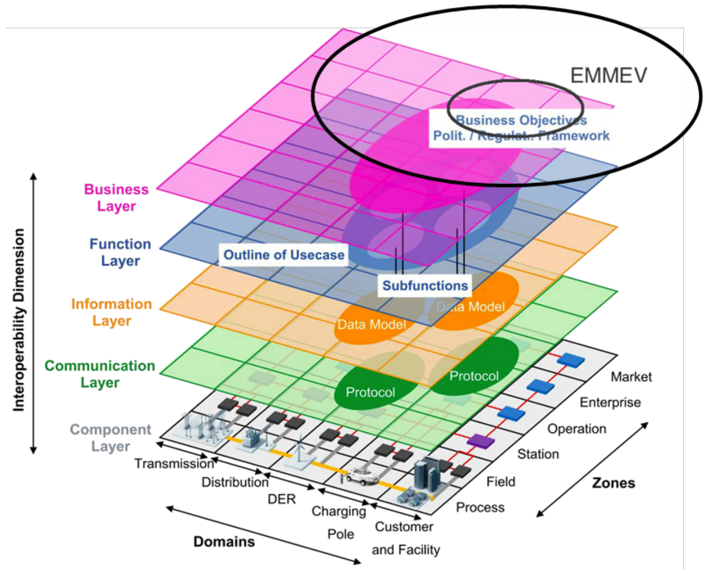


**Figure 21: EMMEV in SGAM**

This clarifies more about EMMEV and which area the modeling has occurred. In the next two sections of this thesis, two legs of the model, electricity market and LCFS, are described.

## 3.6 EMMEV day-ahead electricity market model

EMMEV models day-ahead electricity market. Although EVs can perfectly contribute in both power regulation market [73] [74, 75] [75], in EMMEV only the participation of EVs in day-ahead market is being considered. In order to start the modeling steps and results, first the modeling environment in which the agents are playing is described and then the agents and their roles and flexibility are explained.

The environment is a regular electricity market [74] in which technological, economic and regulatory sub-environments do exist. The three sub-environments are described in the following paragraphs.

From technological perspective, the power system in many countries is divided into three sectors: generation, transmission and distribution. The generation technologies are very different and new technologies for generation of electricity, especially from environmentally-friendly resources such as wind and wave, are being discovered and being used [76].

In EMMEV, the generation units participate in the electricity market to sell their generated electricity. The generation units have different technologies. The transmission system consists of high-voltage lines and substations. It is the most conservative part of the power system business where mostly state-owned companies own the assets (in modern times, this has also being privatized although it is still a natural monopoly). In EMMEV, the transmission system affects the system prices by its congestion on the high voltage lines, which in turn leads to different prices in different price areas [77].

Most of the customers are connected to the distribution grid. Most of innovation and changes in the power system technologies happen in the distribution grid. Private companies can own the distribution grid while independent regulators have very tight supervision on their operation, performance and tariffs.

In the EMMEV, the environment in ABM is where the generation units (conventional and renewables) can sell their electricity. The transmission line will impose congestions that cause different electricity prices in different areas. The mechanism of selling electricity is described in the following paragraphs.

Based on the described environment, there are agents, which are ESCos, are modeled based on ABM where the agents try to maximize their profit. In the day-ahead part of EMMEV, the agents own generation units and are eligible to participate in the electricity market in order to sell their electricity.

The modeling steps are as follows: The agents in model have the option to bid in the electricity market. Then there will be a market settlement in which all the supply and demand curve is realized. The electricity price is set by crossing the demand and supply curve. And based on the electricity price, the units that pitch their bidding price lower than electricity price are eligible to sell, and those with a bidding price higher than electricity price cannot sell. The actions in the day-ahead electricity market model are shown graphically in Figure 22.

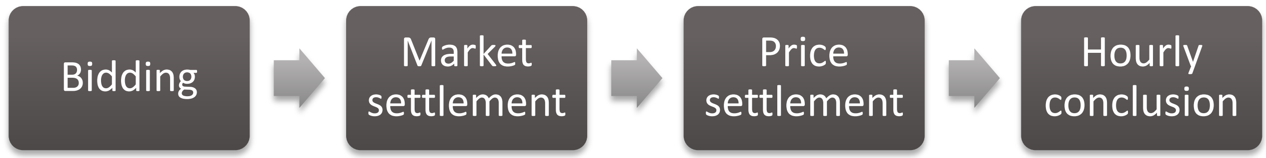


**Figure 22: Actions in day-ahead electricity market model**

The actions and their responsible entities and their flexibilities are shown in Table 10.

**Table 10: Actions and responsible entity**

| Action | Responsible entity |
|---|---|
| Bidding | Generation units owners (agents) |
| Market settlement | Market operator |
| Price settlement | Market operator |
| Hourly conclusion | Market operator |

### 3.6.1 Bidding

Part of the agents' revenue comes from their generation units. In addition, as described above in this chapter, the agents only address day-ahead electricity market, and the agents own generation units and can participate in the electricity market to sell their electricity. The agents need to bid in an electricity market in order to sell their generated electricity. The agents bid at each hour by specifying the amount of electricity that they can generate (in MWh) and their price (in €/MWh). It is assumed that the agents are in a perfect competition environment. Therefore, they bid based on their operational cost. Renewable generation has usually priority in the dispatch (receiving a feed in tariff) and is considered for market bids purposes that this offer for renewable generation "offers" a price.

### 3.6.2 Market settlement

Based on their operational cost, a supply curve is formed as is shown graphically in Figure 23. In EMMEV, the demand can have some elasticity  due to increase in storage, micro generation and home automation. The supply function with the demand curve is shown in Figure 23.

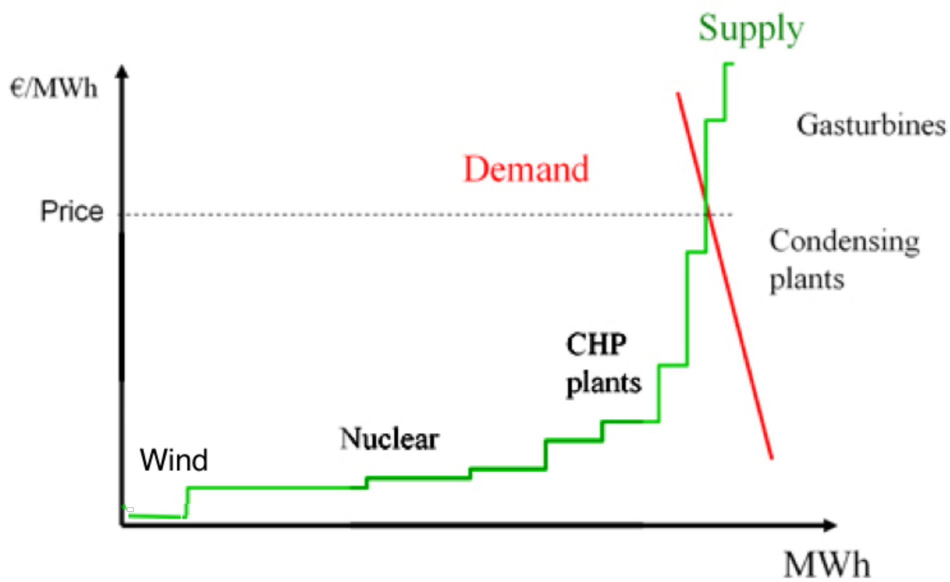


**Figure 23: Demand and supply curve and at each hour of operation [78]**

As shown in the figure above (the figure is indicative and not representing the test system in this thesis), the supply curve (shown in green) are the offers made by the generating units . Demand in the figure above has some elasticity [79]. The renewable power generation can come with feed in tariffs, so they have priority to be dispatched. The elasticity of the demand is dependent on customer behavior. In the liberalized market with more technology and regulation shift to use flexibility, the demand elasticity is more probable and that's why demand elasticity is added in this thesis [80]. In the next section of this thesis, the process ending in price settlement is described.

### 3.6.3 Price settlement

The price is settled based on the bidding units and the demand curve. In EMMEV, the piece of code which described the price settlement is shown in Figure 24.


```java
public void calculateElectricityPrice(){
    for (int area=0 ; area<4 ; area++){
        hourlyElectricityPriceMap.put(area, new ArrayList<Double>());
        List<Double> hourlyElectricityPrice = new ArrayList<Double>();
        for (int i=0 ; i<24 ; i++){
            double supply = 0;
            int j = 0;
            // Area 1
            if (area == 0){
                while (j<globalPlanner.genInArea11.size() & supply<globalPlanner.getHourlyDemand(i, area, 3)){
                    supply = supply + globalPlanner.genInArea11.get(j).generationCapacity;
                    j = j + 1;
                }
                //System.out.println("\nDemand : " + globalPlanner.getHourlyDemand(i, area, 3));
                Double lastGeneration = globalPlanner.getHourlyDemand(i, area, 3) - supply + globalPlanner.genInArea11.get(j-1).generationCapacity;
                if (j<=globalPlanner.genInArea11.size() & supply>=globalPlanner.getHourlyDemand(i, area, 3)){
                    hourlyElectricityPrice.add(globalPlanner.genInArea11.get(j-1).getMarginalCost());
                }
                else{
                    hourlyElectricityPrice.add(1000.0);
                }
```

**Figure 24: Price settlement in EMMEV model**

There is always one single unit which is marginal units and the operational cost of the marginal unit will set the price.

### 3.6.4 Hourly conclusion

The generation units (which are owned by agents) benefit from the settled price. The benefit per unit of electricity generation is the difference between the settled price and their own operational cost. The benefit aims to cover the investment cost as well.

```java

                ////////////////////////////////////      Add Profit     ////////////////////////////////////////////////////////
                for (int p=0 ; p<j ; p++){
                    Double profit = 0.0;
                    if (p == j - 1){
                        profit = (hourlyElectricityPrice.get(i) - globalPlanner.genInArea11.get(p).variableCost)*lastGeneration;
                        globalPlanner.entities.get(globalPlanner.genInArea11.get(p).entity-1).profitGE = globalPlanner.entities.get(globalPlanner.genInArea11.get(p).entity-1).profitGE + profi
                    }
                    else{
                        profit = (hourlyElectricityPrice.get(i) - globalPlanner.genInArea11.get(p).variableCost)*globalPlanner.genInArea11.get(p).generationCapacity;
                        globalPlanner.entities.get(globalPlanner.genInArea11.get(p).entity-1).profitGE = globalPlanner.entities.get(globalPlanner.genInArea11.get(p).entity-1).profitGE + profi
                    }
                }
            }
            // Area 2
```

**Figure 25: Hourly conclusion**

## 3.7 Behavior of agents in EMMEV

Each ESCo (agent in EMMEV) has revenue and costs. It is important to mention that the agents cannot have both generation and retailing. There are two type of ESCo in the thesis:

1. ESCo1: Retailing and Aggregation and LCFS services
2. ESCo2 (Genco): Providing generation services.

The total profit of each agent is defined as the subtraction of revenue from cost.

$$P_{ESCo} = R_{ESCo} - C_{ESCo} \quad \text{Equation 1}$$

$$P_{Genco} = R_{Genco} - C_{GENCo} \quad \text{Equation 2}$$

The revenue of each type of ESCo has three parts from three different energy services:

$$R_{ESCo} = R_{Retailing} + R_{EV\ aggregation} + R_{LCFS} \quad \text{Equation 3}$$

Due to unbundling in the electricity market, an agent can either provide generation or other services (retailing, aggregation and LCFS).

The revenue from generation is set by the spot price of electricity and the amount generated electricity. The revenue from retailing is also dependent on the price patterns offered to the end consumers and the amount of consumption per hour. The EV aggregation services also make revenue by the sale of electricity to EV owners. They can make profit by offering different price patterns to the EV drivers. The ESCos will have some revenue from LCFS market which will be discussed in the next phases of model development.

$C_{GENCo}$ is the cost for each ESCo. The electricity generation costs, cost of buying electricity for retailing and cost of buying electricity for EVs are the main costs of ESCos. The ESCos will have some costs from LCFS market which will be discussed in the next parts of this thesis.

ESCo1 will make profit by selling electricity with different price patterns (defined as input). In other words, it is assumed that ESCos, at this stage of the work, do not make any profit from generation and retailing services. The costs are not considered at this stage of development either. In the next phases of development, all other revenues and costs will be added to the model.

In the EMMEV, the number of vehicles and EVs are calculated by the population, and this will be outlined in more detail in next chapters. In this thesis, only slow charging at home and in public (including work charging) and connected to the distribution LV networks are considered.

Regarding the procedure for slow-charging batteries, the PHEVs can be considered as simple loads when their owners simply demand that batteries must be charged with a fixed rate, which corresponds to a dumb charging; or as dynamic loads, if their owners demand a time interval for the charging to take place, allowing some EV management structure to control the charging rate under a smart charging framework. From the grid point of view, the second approach yields more benefits since the EV management structure will control the charging process by reducing/increasing the charging rate according to the system operating conditions, so that charging can be distributed during valley hour periods and at times when there is large renewable power generation.

Agents in EMMEV know about the structure of Electricity Market and LCFS and also have to communicate with other agents in Repast. An agent is able to communicate only about facts that can be expressed in some ontology. This ontology must be agreed and understood among the agent community (or at least among some of them) in order to enable each agent to understand messages from other agents.

The studied behavior of agents in EMMEV are in three main categories of behaviors as below:

1. Profit maximizing
2. Banking strategy
3. Shift toward low-carbon fuel

These three behaviors of the agents and their relations to each of the services provided by agents are summarized in Table 11.

**Table 11: The relation between agents studied behaviors and agents provided services**

| | Profit maximizing | Banking Strategy | Shift toward low-carbon fuel |
|---|---|---|---|
| Power generation | ✓ | ✗ | ✗ |
| Electricity retailing | ✓ | ✗ | ✗ |
| EV aggregation | ✓ | ✗ | ✓ |
| LCFS | ✗ | ✓ | ✓ |

In each of the three revenue cases (generation, retailing and EV aggregation and LCFS), the agents interact differently. In, Figure 26 the interaction of agents in generation is shown.

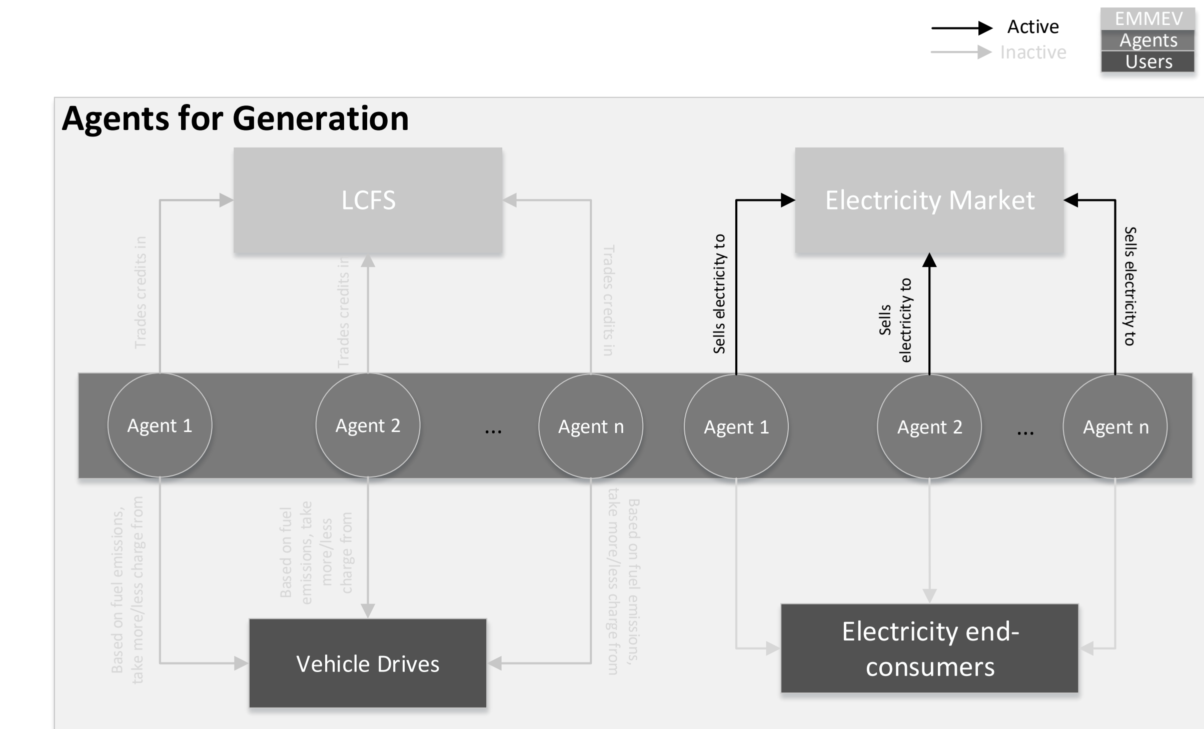


**Figure 26 Agents interaction for generation in electricity market (dark black lines shows active interaction)**

As shown in the above figure, the agents sell their generated electricity in the electricity market. It is assumed that the agents have balanced share of market and cannot influence prices. The electricity prices are set by passing demand curve through the generation curve at each hour.

Retailing and EV aggregation create similar agents' interactions as it is shown in Figure 27.

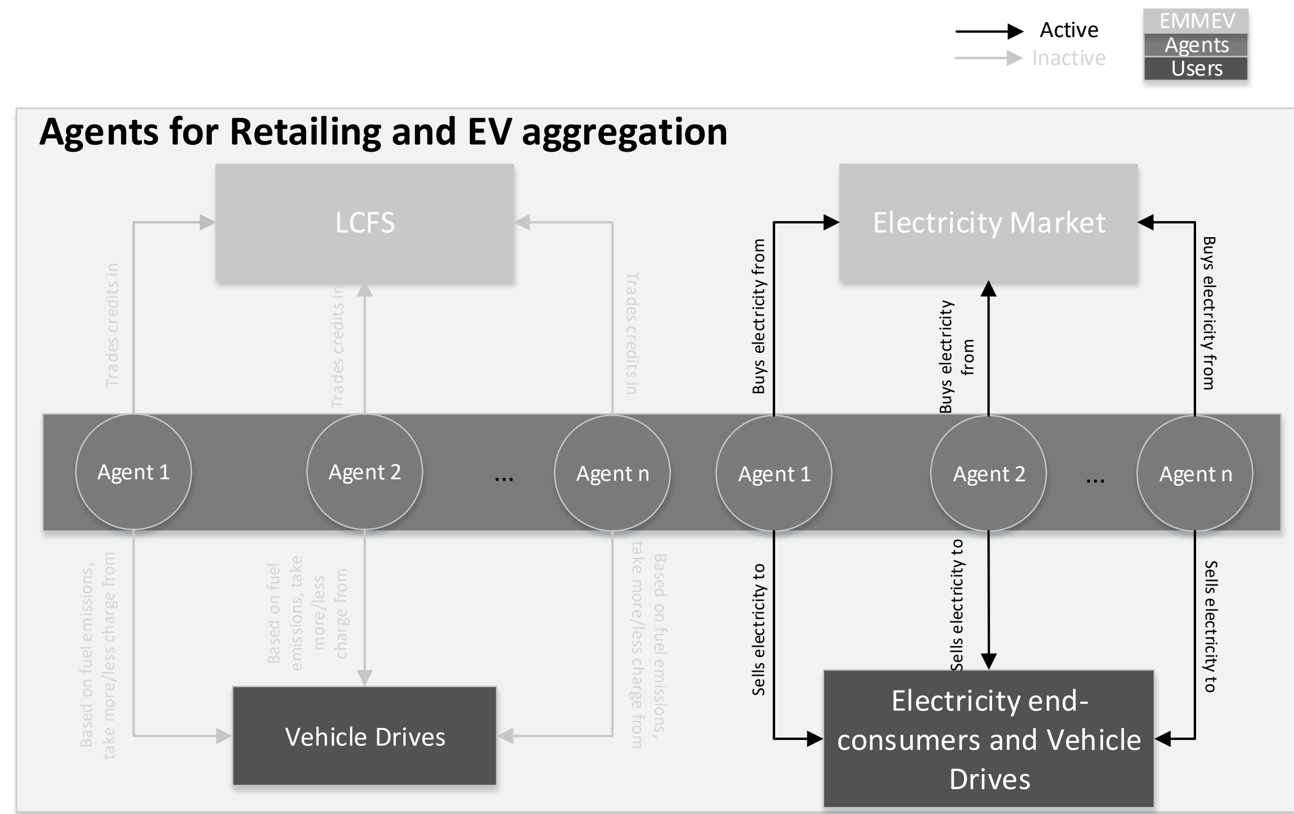


**Figure 27 Agents interaction for retailing in electricity market (dark black lines shows active interaction)**

In this energy service, the agents buy their electricity from the electricity market and sell it to the end users. This is valid for the electricity to be sold for any industrial, commercial and residential application as well as for EVs to charge their batteries. The agents also interact in the LCFS part of EMMEV. This has been visualized in Figure 28.

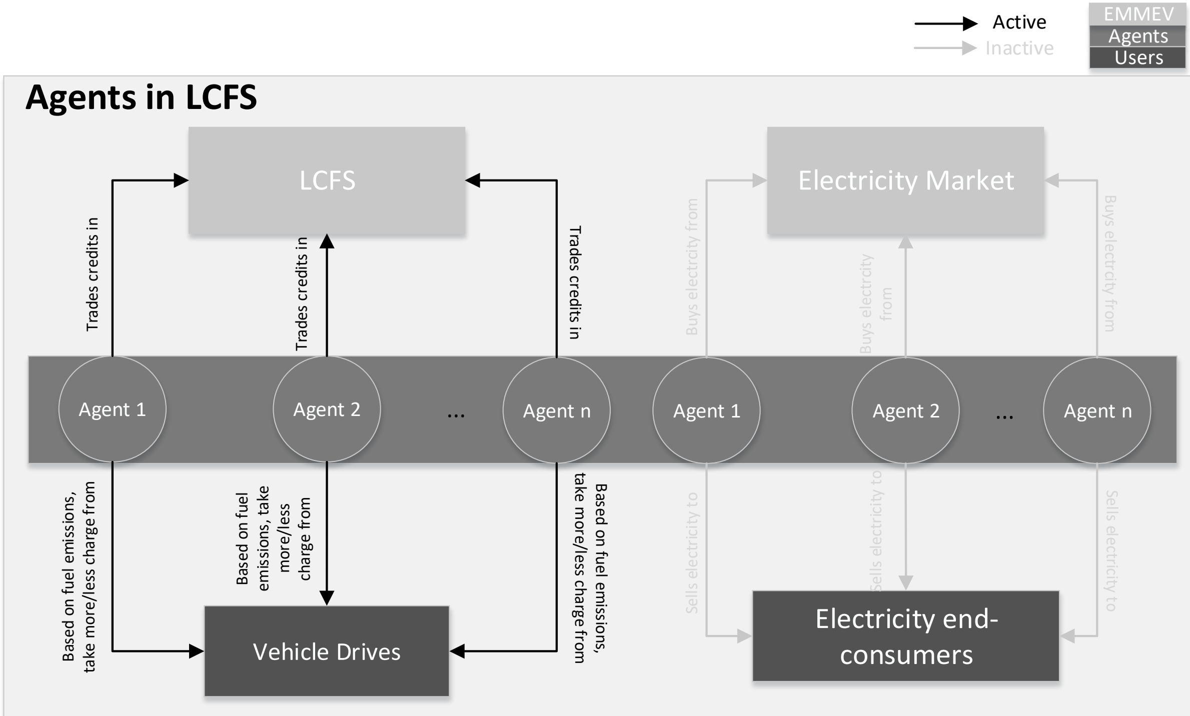


**Figure 28 Agents interaction in LCFS (dark black lines shows active interaction)**

In this service, the agents interact in the LCFS market to trade their credits. The agents also charge the vehicle drivers less or more based on the emissions from each specific fuel sold and the credit they get for each specific fuel.

Models such as EMMEV create an understanding in this complex, interrelated and multidisciplinary area. This understanding serves the regulators and policy makers to guide the transportation toward low-carbon alternatives.

The agents are all profit maximizing for all the four services. For the power generation, the agents bid in the electricity market at their marginal cost and sell at the market price. The agents in this model cannot use their market power not to sell when the generation is available. Regarding the retailing, the agents sell based on a pattern in which the hourly electricity prices are higher during peak hours when the demand is higher. For the EV aggregation, the EV drivers need to pay to the agents based on the same price pattern as in retailing so the agents maximize their profit.

In the LCFS, the agents utilize a banking strategy of their certificates to maximize their profit. The banking strategy is based on a perspective of the future certificate prices.

The revenue from LCFS can be used to shift from high-carbon fuels to low-carbon fuel distribution such as electricity. This means that the profit from LCFS can to be invested in the infrastructure to pave a way for a shift to low-carbon fuel. The main challenge for EVs is if the infrastructure should come first to have more EVs or vice versa.

## 3.8 Congestion Management

Congestion in power systems means that the transmission networks fail to transfer power based on the load demand [81]. Overloading transmission networks or network congestion is result of increasing generation units in different location and also the development of deregulated power systems [77]. In serious cases, congestion might damage the power system. As important part of deregulated electricity market, these problems should be managed using Congestion Management methods. Several methods have been proposed to manage congestion in different researches [82] [83] [84]. In this section of the thesis, the congestion management methods are introduced [85] and the method used in EMMEV is described.

The congestion management is being described in a proper manner in [85] and in this thesis is summarized in Table 12.

Technical methods are cost-free methods which take into consideration outages in congested lines and do not cause economic effect. Some methods are the use of FACTS and the operation of transformer taps or phase shifters. Non-technical methods or non-cost free methods take into consideration security-constrained generation dispatches, network security factors methods, congestion pricing, and market-based methods. A few common methods are auctioning, market splitting, counter trading, re-dispatching, load curtailment, nodal pricing and zonal pricing. There are some other non-market based methods but still non-cost free such as first come, first serve and pro-rata [85].

**Table 12 Summary of different congestion management**

| Type of Method | | Title of Method | Description |
|---|---|---|---|
| Technical | | Outage of congested line | The congested line is disconnected. |
| | | Transformer tap changers | Tap changer is used to control the voltage and eventually the load |
| | | Operation of FACTS devices | A flexible alternating current transmission system to control current and eventually the load |
| Non-technical | Market-based | Auctioning | Specially for large controllable loads [86] |
| | | Market Splitting | Giving a price signal that clearly informs the market participants about the congested areas [87] |
| | | Counter Trading | The network operator counter-trade against the flow of congestion [88] |
| | | Re-dispatching | Altering the generation and/or load pattern in order to change physical flows in the transmission system and relieve a physical congestion [89] |
| | | Load curtailment | curtailing a small portion of the non-firm transactions [90] |
| | | Nodal pricing | Considering all the transmission constraints in the day-ahead market. No for European market [91] |
| | | Zonal pricing | Zonal pricing aggregates nodes into zones with uniform prices. Ideally, zonal pricing should consider all transmission constraints and the nodal prices inside a zone should be the same [92] |
| | Non-market based | First come, first serve | Any remaining or newly released capacity after the day-ahead market clearing is allocated for free, on a first-come first-served basis [81] |
| | | Pro-rata | Curtailing in case of congestion according to the ratio, existing capacity/requested capacity [93] |

The most efficient, social benefit maximizing congestion management is nodal pricing. In this case, prices in each node are different and directly reflect limited transmission capacity and possible congestion between the nodes. This cannot applicable in European interconnected power grid while in the US, nodal pricing has been used. Nodal pricing can prevent an overload of transmission lines and in addition, it can well find optimal investments in the long-run. However, an important difficulty of nodal pricing is the high number of calculated prices [94].

A single congested transmission line may yield nodal prices that differ at every node of the network. Therefore, network nodes are sometimes partitioned into price zones that share a common price. This approach is referred to as zonal pricing [94]. Zonal pricing is also named as market splitting [95].

In this thesis, a zonal pricing is considered for development of EMMEV. A pricing zone is defined as the largest geographical area within which market participants are able to trade energy without capacity allocation. These zones are defined by the regulator and/or the transmission system operator (TSO) and in this thesis corresponds to the *regions* defined in each country. The price differentials between the zones reflect the grid congestion between the zones [96].

## 3.9 Summary and Discussion

This chapter concludes a description of how EMMEV is being modeled. EMMEV is an agent-based model for electricity market with EVs and LCFS. Agents in EMMEV provides four services:

- Power generation
- Electricity retailing
- EV aggregation
- LCFS

The agents are profit maximizing units in which their behaviors in the following three behavior categories are studied:

1. Profit maximizing
2. Banking strategy
3. Shift toward low-carbon fuel

EMMEV is a platform where different policy schemes to decrease carbon emissions in transportation and their influence on Electricity Market can be tested. In the next chapter, a test system to test EMMEV is described. Then all three behaviors of the agents are studied in that test systems and the results are presented.

# Chapter 4
# Test System for EMMEV

In this chapter of the thesis, a test system which was used to test EMMEV is described. The current test system is representing an electricity market. There are two countries in the market. Both countries have two price regions. There are 5 ESCos (agents in agent-based modeling) operating in different regions of the two countries. The ESCos, as described in the last section, can provide power generation and EV aggregation services.

As depicted in Figure 12, there are some inputs and outputs in the system. The inputs are presented in detail. EMMEV is tested for 15 years (2016-2030) by means of the test system.

The population of the countries defines the electricity consumption and number of vehicles. This structure is depicted in Figure 29.

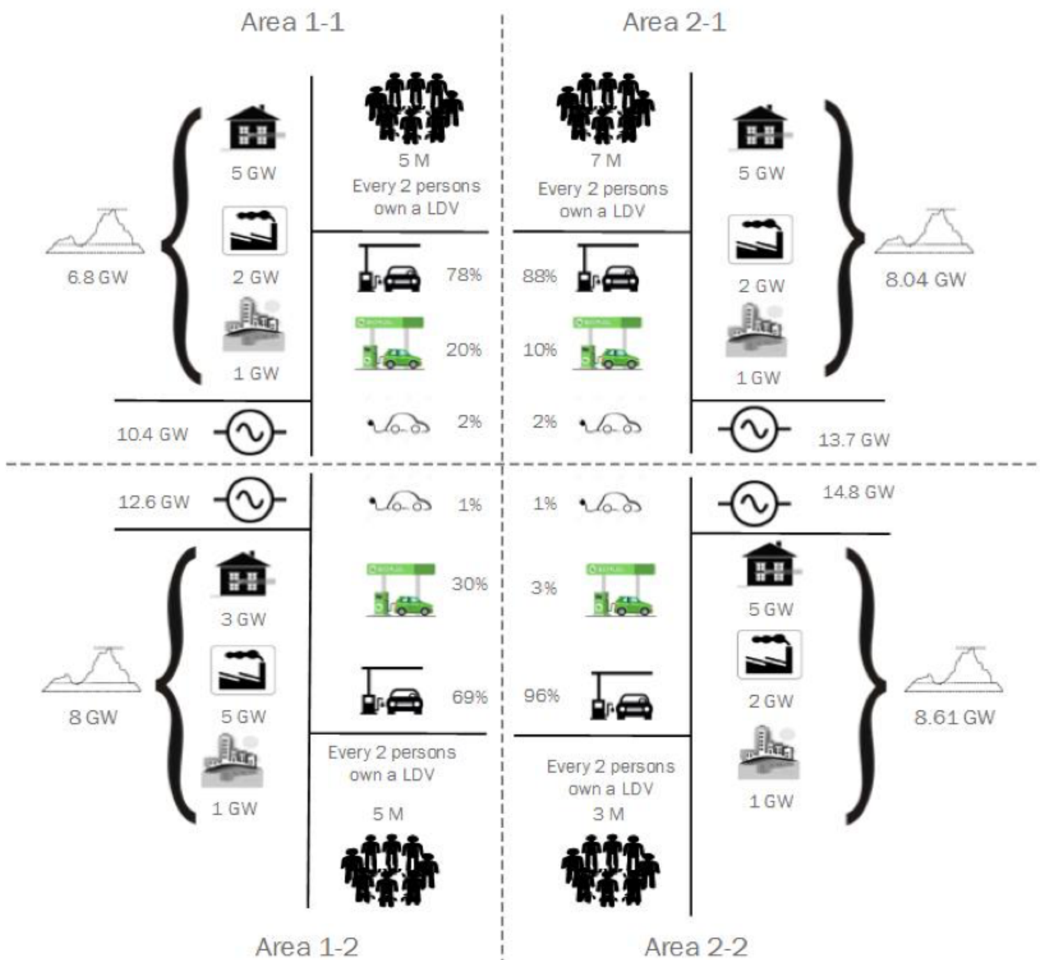


**Figure 29 Structure of the test system**

Country 1 has a population of 10 million people in 2016. It is assumed that every 2 persons have a LDV. This is a valid number for countries like Sweden and Portugal [97]. There are three categories of vehicles in the test system: gasoline vehicles, biofuel vehicles and electric vehicles. The percentages of the vehicles in each category are based on Sweden and Portugal. However, these are part of the basic assumptions in the test system and the numbers are not exactly the same for the abovementioned countries. The parameters used in the test system are described in Table 13. The parameters fall into three categories: assumptions, referenced data or derived-from-referenced data. The 'assumed parameters' are made based on an assumption. The selected value for the 'assumed parameter' has minor impact on the test system. The referenced parameters are made based on a referenced data or scientific paper. Finally, the parameters which are derived from referenced data are different from referenced data, as the first is customized based on the test system and the second is taken directly from the reference.

**Table 13: Description of the parameters in the test system**

| | General (G) | | Electricity consumption (EC) | | | Electricity generation (EG) | | Mobility (M) | |
|---|---|---|---|---|---|---|---|---|---|
| | G1 | G2 | EC1 | EC2 | EC3 | EG1 | EG2 | M1 | M2 |
| | Number of countries in the electricity market | Population in each country | Electricity consumption per person | Peak electricity consumption | Load patterns | Power generation capacity | Share of different type of generation | Number of LDV per person | Share of each type of vehicle |
| Assumption | √ | √ [98] [99] | √ [98] [99] | √ [98] [99] | | √[1] | √[98] [99] | | |
| Referenced | | | | | √ [8] | | | √ [98] [99] | |
| Derived from referenced data | | | | | | √ (EC2, EC3) | | | √ (M1) |

[1]It is assumed that there is always enough generation capacity to meet the demand. Therefore, it is impossible to have infinite electricity price.

The General parameters (G) are number of countries and population in each country. The number of countries (G1) is an assumption in the test system. The population (G2) is based on data to which reference is made in Table 13.

There are three main parameters in Electricity Consumption (EC); electricity consumption per person (EC1), peak electricity consumption (EC2) and load patterns (EC3). Electricity consumption per person, as well as peak electricity consumption, are referenced data and the reference is mentioned in the above table. The load patterns are also taken from the same reference shown in the table above. In the following sections of the thesis, first the electricity sector data and then the transportation data are presented.

It is important to highlight that in this thesis, it is assumed that transmission capacity is available between each pair of areas.

## 4.1 Electricity market

First, the load structure is described. Then the generation units in each area are presented and described. It is important to mention that the agents cannot have both generation and retailing. The attribute related to either demand or generation should be always zero. This is due to unbundling of responsibilities in the electricity market. In addition, the transmission capacity available between each pair of areas.

### 4.1.1 Load

Utilities around the world have different categories for loads. These categories will define how they will charge the customers. For example, E.ON, a major utilities in Europe, for its business in Sweden has two categories of customers: private and commercial [100]. There are sub-categories connected to the load which varies, depending on the size of the load.

In this test system, the loads are categories in three categories: residential, commercial and industrial [101]. The load profile (percentage of the peak load) related to each category is depicted in Figure 30 [8].

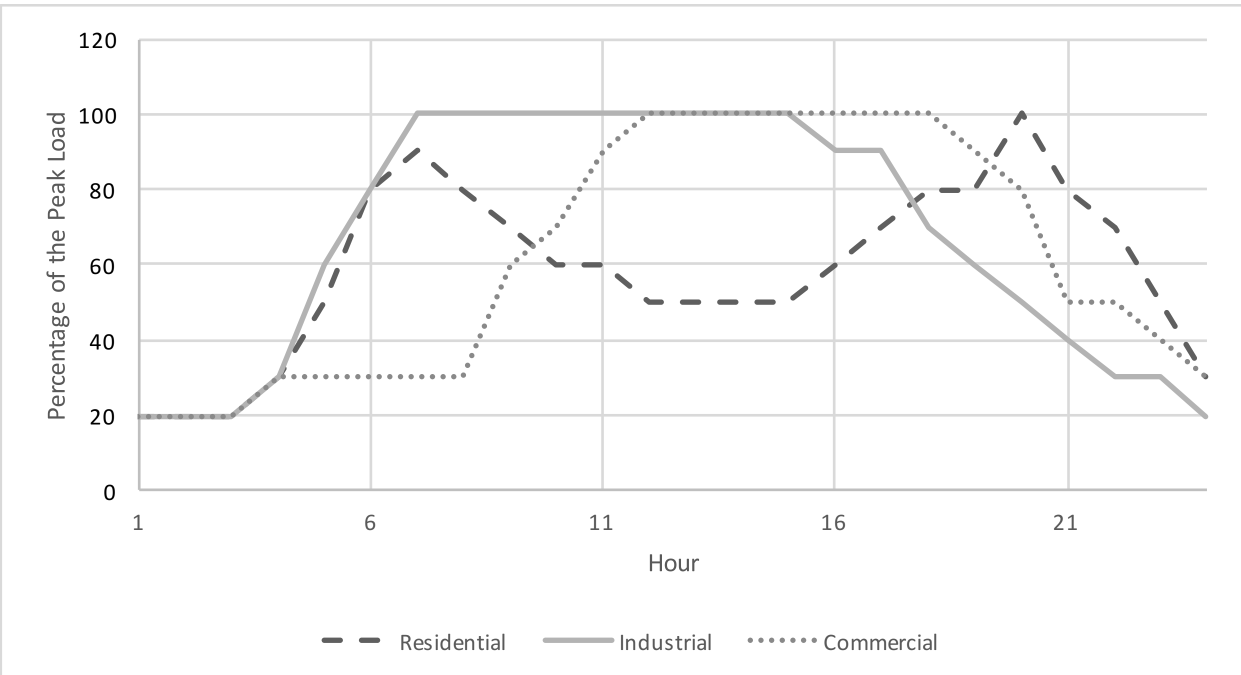


**Figure 30 Load profiles**

These load profiles are used to make the load curves in each area. The peak load in each area is summarized in Table 14.

**Table 14: Peak loads in each area**

| Area | Residential (MW) | Commercial (MW) | Industrial (MW) |
|---|---|---|---|
| Area 1-1 | 5000 | 2000 | 1000 |
| Area 1-2 | 3000 | 5000 | 1000 |
| Area 2-1 | 6000 | 3000 | 1300 |
| Area 2-2 | 6000 | 3000 | 700 |

Based on the above data, the total load curves in each area are shown in Figure 31.

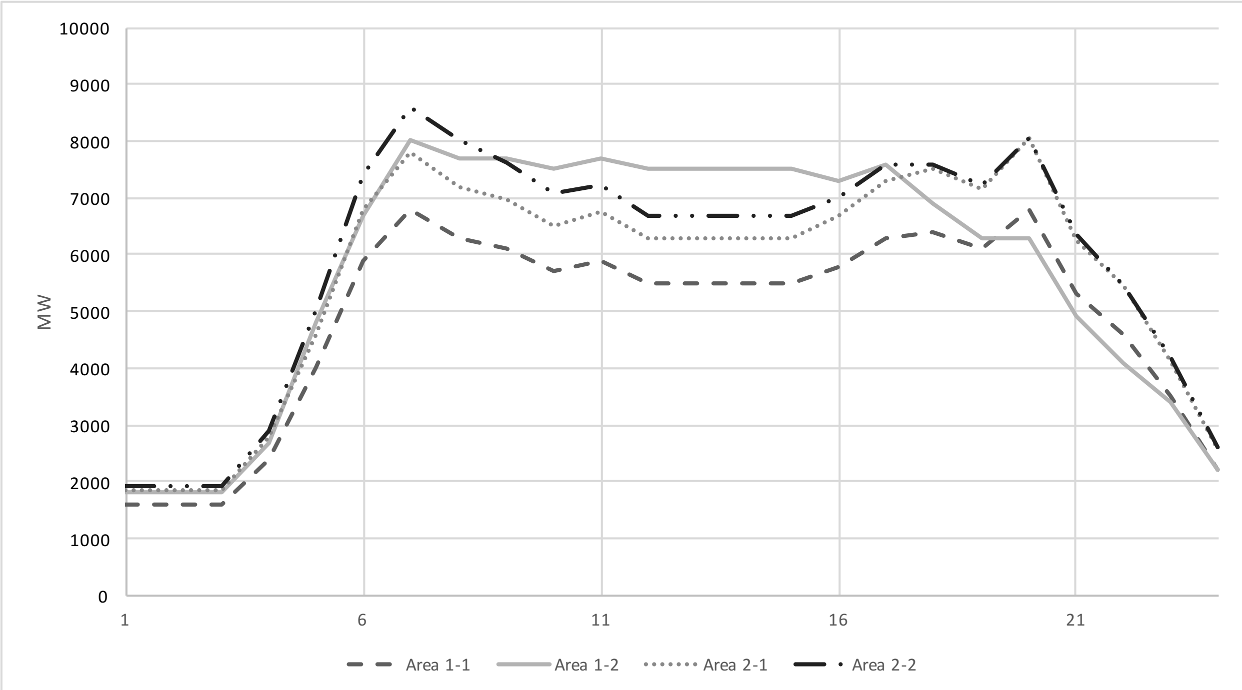


**Figure 31: Load curves in each area**

The figure above is a sample day of yearly simulation data. This load data is used for testing EMMEV which are the same in both regions.

### 4.1.2 Elasticity of Demand

The concept of elasticity is borrowed from physics and engineering and it is used to measure responsiveness of to a force [102]. In economics, the force is some market force such as a change in price or income. Elasticity is measured and calculated as a percentage change/response in both engineering applications and in economics. The benefit of measuring in percentage terms is that the units of measurement do not play a part in the value of the measurement and therefore allows direct comparison between elasticities. The Price Elasticity of Demand (PED) measures the change in demand for a good in response to a change in price. PED is described as below:

$$PED = \frac{\text{\% of change in quantity demanded}}{\text{\% change in price}} \qquad \text{Equation 4}$$

For example, if the price of gasoline increased say 50 cents from an initial price of \$3.00 and generated a decline in monthly consumption for a consumer from 50 gallons to 48 liters, we calculate the elasticity to be 0.24. The price elasticity is the percentage change in quantity resulting from some percentage change in price. A 16 percent increase in price has generated only a 4 percent decrease in demand: 16% price change → 4% quantity change or 0.04/0.16 = 0.24. This is called an inelastic demand meaning a small response to the price change. This comes about because there are few if any real substitutes for gasoline; perhaps public transportation or a bicycle. Technically, of course, the percentage change in demand from a price increase is a decline in demand thus price elasticity is a negative number [102] [103].

In the case of electricity as a commodity, elasticity is used to measure the responsiveness of consumers to mainly three measures; electricity price, family income and cross-price (substitute good) [104] [105]. This has been summarized in Table 15.

**Table 15 Various elasticities for electricity demand**

| Demand elasticity type | Elasticity measure | Elasticity measured against | Sector |
|---|---|---|---|
| **Price** | Electricity demand | Electricity price | Residential, Commercial, Industrial |
| **Income** | Electricity demand | Income of family | Residential |
| **Cross-price** | Electricity demand | Price of alternative energy | Residential, Commercial, Industrial |

In this thesis, electricity demand elasticity against electricity price is considered. Demand elasticity for areas with dense energy consumption (industrial and commercial) is higher than in residential areas [104] [105] [106]. In addition, the higher load will cause higher demand elasticity [105]. Based on above two principles, the demand elasticity for each area on the test system for EMMEV is estimated. In [107] [106], the demand elasticity for different countries has been calculated and based on that calculations, the short-term demand elasticity for each area is estimated in Table 16.

**Table 16 Short-term electricity demand elasticity in each area**

| Area | Residential (MW) | Demand elasticity | Commercial (MW) | Demand elasticity | Industrial (MW) | Demand elasticity |
|---|---|---|---|---|---|---|
| Area 1-1 | 5000 | -0.55 | 2000 | -0.5 | 1000 | -0.8 |
| Area 1-2 | 3000 | -0.5 | 5000 | -0.7 | 1000 | -0.7 |
| Area 2-1 | 6000 | -0.6 | 3000 | -0.65 | 1300 | -0.9 |
| Area 2-2 | 6000 | -0.6 | 3000 | -0.65 | 700 | -0.85 |

The above elasticities are calculated using the double-log form of the demand function by average income and average electricity price [106]. The PED is the percentage change in quantity demanded in response to a one percent change in price. The PED coefficient is usually negative, although economists often ignore the sign. Demand for a good is relatively inelastic if the PED coefficient is less than one (in absolute value). Demand for a good is relatively elastic if the PED coefficient is greater than one (in absolute value). Demand for a good is unit elastic when the PED coefficient is equal to one. As shown in Table 16, the demand elasticity in industrial areas is larger. This is due to the fact that industrial loads can provide larger flexibility and they would get paid for such flexibility.

The demand elasticity data from Table 16 is used to create demand curves shown symbolically in Figure 23. The respective demand elasticity at each hour is calculated by weighted average of demand elasticity of all load values of different types (residential, commercial and industrial) and their respective PED.

### 4.1.3 Generation units

Generation units are important part of the model. The agents (ESCos) in EMMEV can also provide power generation services. The total generation capacity in each area is summarized in Table 17.

**Table 17: Generation capacity in each area**

| Area | Generation capacity (MW) |
|---|---|
| Area 1-1 | 10400 |
| Area 1-2 | 12600 |
| Area 2-1 | 13700 |
| Area 2-2 | 14800 |

As described in Chapter 2, there are two layers in EMMEV: geographical and agent. The generation units in the other layer of the system are owned by agents (ESCos). The power generation ownership of each agent is shown in Table 18.

**Table 18: Generation units owned by different agents**

| Agent number | Generation unit (MW) |
|---|---|
| 1 | 24900 |
| 2 | 0 |
| 3 | 20700 |
| 4 | 0 |
| 5 | 5900 |

The details of each generation unit in different areas and owned by different agents is shown in Appendix 1. The Renewable generation bid at their variable cost described in Appendix 1. The market will dispatch the lowest price and the support schemes to renewable is not the focus area in this thesis.

## 4.2 LDV Transportation

The second part of the test systems is the LDV transportation system. The population in each area set the number of LDV in each region. The test system has been shown graphically in Figure 29. There are three types of LDV in the system:

- Gasoline Vehicles
- Biofuel Vehicles
- Electric Vehicles

The number of vehicles in each area is shown in Table 19.

**Table 19: Number of vehicles in each region in 2016**

| Country number | Region number | Total population (k) | Number of LDV (k) | Percentage of Gasoline Vehicles | Percentage of Biofuel Vehicles | Percentage of EVs |
|---|---|---|---|---|---|---|
| 1 | 1 | 5000 | 2500 | 78 | 20 | 2 |
| 1 | 2 | 5000 | 3000 | 69 | 30 | 1 |
| 2 | 1 | 7000 | 2800 | 88 | 10 | 2 |
| 2 | 2 | 3000 | 900 | 96 | 5 | 1 |

Each of the vehicles is described in more detail in the following sections of the thesis.

### 4.2.1 Gasoline and Biofuel Vehicles

The emissions for gasoline and biofuel are summarized in Table 20 [108].

**Table 20 Emissions in biofuel and gasoline transportation**

| Vehicle type | $gCO_2e/MJ$ | Driving distance per year (km) | Kg $CO_2$/year/vehicle |
|---|---|---|---|
| Gasoline | 98 | 12000 | 2100 |
| Biofuel | 40 | 12000 | 860 |

### 4.2.1 Electric Vehicles

There are three types of EVs in the test system. These are summarized with their specifications in Table 21. The selection of types of EVs is in line with the definition of EV types in European project called MERGE [109] and in [58], as described in the following table.

**Table 21 Types of EVs in the test system**

| Battery capacity (MWh) | Charging rate (MWh/h) | Start time | Parking duration (hours) | Primary SOC (%) | Final SOC (%) | Agent ID | country | Region ID | Percentage of this EV type in the whole fleet |
|---|---|---|---|---|---|---|---|---|---|
| 0,008 | 0,003 | 17:00 | 4 | 0 | 1 | 2 | 2 | 1 | 7 |
| 0,008 | 0,003 | 17:00 | 4 | 0 | 1 | 2 | 1 | 2 | 26 |
| 0,008 | 0,003 | 18:00 | 4 | 0 | 1 | 2 | 2 | 1 | 9 |
| 0,008 | 0,003 | 19:00 | 4 | 0 | 1 | 4 | 1 | 2 | 26 |
| 0,008 | 0,003 | 20:00 | 4 | 0 | 1 | 4 | 2 | 2 | 2 |
| 0,008 | 0,003 | 20:00 | 4 | 0 | 1 | 4 | 1 | 1 | 21 |
| 0,008 | 0,003 | 20:00 | 4 | 0 | 1 | 2 | 2 | 1 | 9 |
| 0,008 | 0,003 | 20:00 | 4 | 0 | 1 | 4 | 2 | 2 | 2 |

It is assumed that all the vehicles are of type M1 with battery capacity of 8 kWh and charging rate of 3 kW [109]. As a normal rate of driving, each car drives 12000 km per year and each car consumes 0.2 kWh of electricity per kilometer. The worst case for the amount of required charging at each charging is considered in which each car arrives with 0% of SOC and wants to be charged to 100% of SOC. Each car needs to be charged 311 times (each time for 8 kWh) in total for 2800 kWh per year [110].

The main target is to decrease emissions from transportation by 10% by the end of 2030. Based on this target, the number of electric vehicles is set in LCFS. The increased number of EVs will increase the load and the increased load will increase the electricity price. The process in which EMMEV follows to get the outputs is visualized in Figure 32.

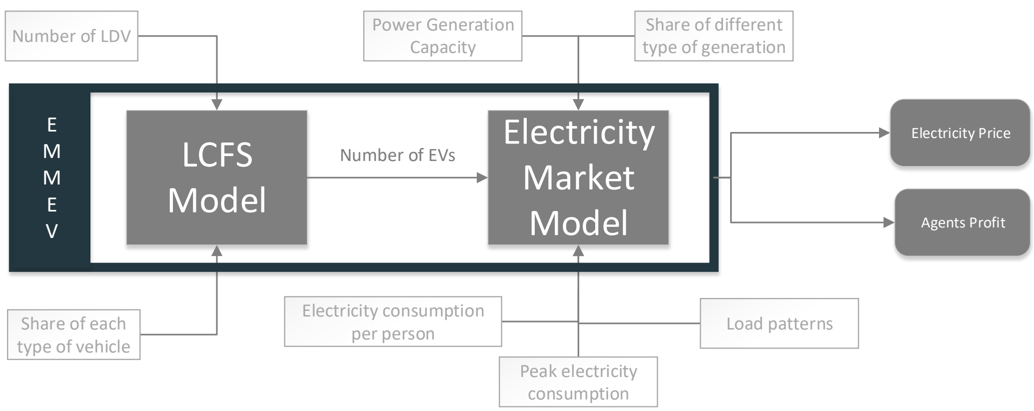


**Figure 32: EMMEV Process**

In this process, the number of EVs the output from the LCFS (EV number) is an input to electricity market. The number of EVs will influence the electricity price. This influence is discussed and analyzed in the next chapter of this thesis.

## 4.4 Agents

As described above, the agents can be either provide generation or retailing/EV aggregation/LCFS. The activity of different agents is shown in Table 22.

**Table 22 Agents activity**

| Agent number | Type of Agent | Generation | Retailing | EV Aggregation | LCFS |
|---|---|---|---|---|---|
| 1 | Genco | ✓ | X | X | X |
| 2 | ESCo | X | ✓ | ✓ | ✓ |
| 3 | Genco | ✓ | X | X | X |
| 4 | ESCo | X | ✓ | ✓ | ✓ |
| 5 | Genco | ✓ | X | X | X |

As shown above, agents 1, 3 and 5 are providing generation and agents 2 and 4 provide retailing/EV aggregation/LCFS. Due to unbundling, the services needs to be separated as designed in the table above.

## 4.3 Summary and Discussion

This chapter of the thesis focuses on describing a test system which is being used to test the EMMEV. This test system is representing an electricity market. There are two countries in the market in this test system and the countries have two price regions. There are in total 5 ESCos (agents in agent-based modeling) operating in different regions of the two countries. The ESCos, as described in the last section, can provide power generation and EV aggregation services. EMMEV is tested for 15 years (2016-2030) by means of the test system. The load factor considered in this thesis is fairly high however, there are renewable generation units in this thesis which are descried in Appendix 1.

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# Chapter 5
# EMMEV Results and Discussions

In this chapter, the results and discussions from both legs of EMMEV (LCFS and electricity market) are being presented and discussed. EMMEV has been tested by the test system described in Chapter 5.

## 5.1 Results and discussions

The agents in the system have the possibility to bank the credits they receive from LCFS [26]. The agents are ESCos. This is a factor by which two scenarios are created in this thesis. In the first scenario, it is assumed that all the agents are cash-constrained which means that they sell their credit by the end of each year. The second scenario is the case in which Agent Number 2 banks the credits and sell them every 5 years in order to influence both the market and gain more.

By regulation, one agent cannot provide generation and other services at the same time and this is shown in Table 22. It is also shown that the agents come in two type; genco or ESCo. In addition, as a test scenario, the case where the agents can bank their LCFS or not. Therefore, the scenarios evaluated in this thesis are summarized as in Table 23.

**Table 23: Scenarios in this thesis**

| Scenario number | Banking | Description |
|---|---|---|
| 1 | No | The agents cannot bank their certificates |
| 2 | Yes | The agents can bank their certificates |

Agents which are eligible to get credits in LCFS market can sell their credits and gain some profit. This profit is meant to be spent on the charging infrastructure and subsidize the sales of EVs. In [24], it is claimed that each 900 € ($1000) increase in financial incentives would cause a country's EV market share to increase by 0.06%. However, the investment in charging infrastructure can be more beneficial to increase the number of EVs; each additional normal charging station per 100,000 residents that a country added would increase its EV market share by 0.12% [24]. That's why in this Thesis, it is assumed that the profit from LCFS is spent in charging infrastructure.

The agents can sell their credits in the Ongoing Credit Market or Credit Clearing Market. However, Clearing Market can hardly happen since the market is not widespread. Therefore, it is assumed that all the credits are sold in the Ongoing Credit Market.

### 5.1.1 Electricity prices

The way how the electricity prices are calculated is presented in section 3.6 and Figure 24. Based on that study, the electricity prices without any EVs charging in the system are shown in Figure 33. In this thesis, a zonal pricing is considered for development of EMMEV. A pricing zone is defined as the largest geographical area within which market participants are able to trade energy without capacity allocation. These zones are defined by the regulator and/or the transmission system operator (TSO) and in this thesis corresponds to the *regions* defined in each country. The price differentials between the zones reflect the grid congestion between the zones [96].

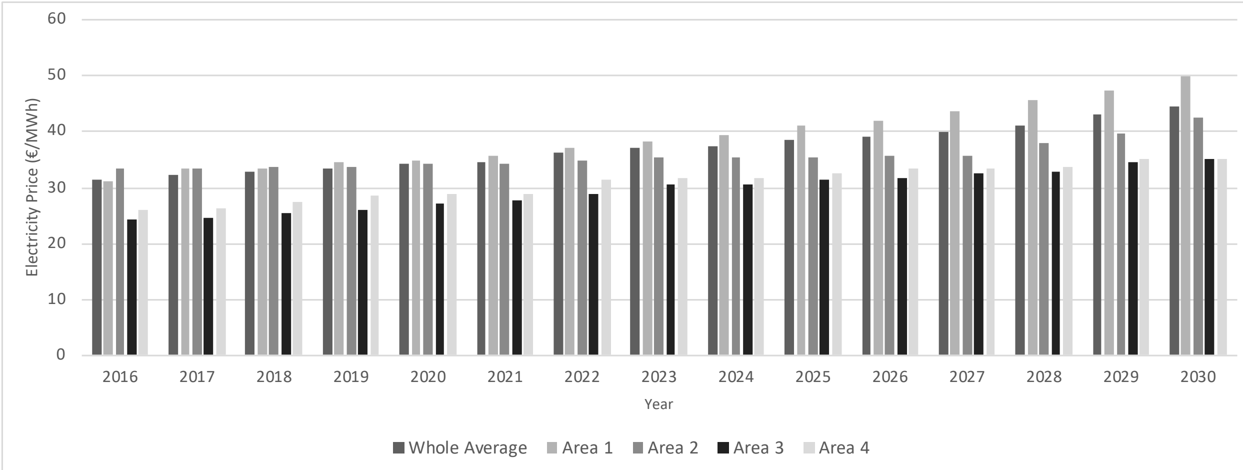



**Figure 33: Annual average electricity prices in four areas and average in all areas from 2016 till 2030**

The electricity prices change because of the changes imposed by LCFS to increase the number of EVs. The average electricity price changes are shown in Table 24.

**Table 24: Electricity price changes in 4 scenarios**

| Scenario number | Banking | Average Electricity Price change compared to the case with no EVs (%) |
|---|---|---|
| 1 | No | 3.47 |
| 2 | Yes | 2.73 |

The changes in the electricity price by LCFS is shown in Figure 34.

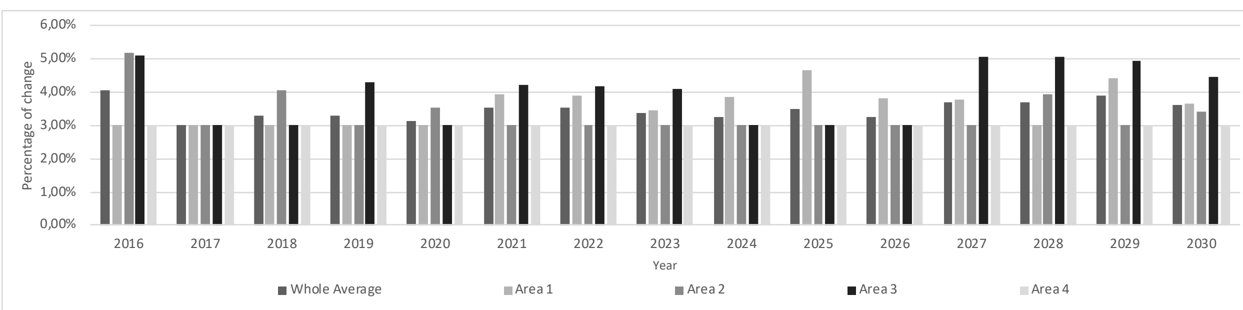



**Figure 34: Change in electricity price with EVs and LCFS supports (no banking)**

In the above figure, the agents cannot bank their certificates from LCFS. However, a banking strategy is implemented in the other simulation in order to investigate the effects of banking. The banking strategy is that the agents can bank their certificates for 5 years. The changes in electricity price with banking strategy is shown in Figure 35.

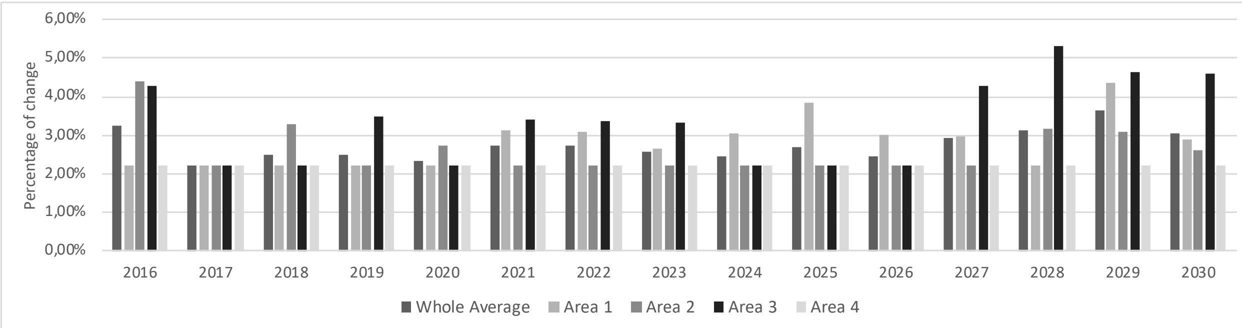



**Figure 35: Change in electricity price with EVs and LCFS supports (banking)**

The size of electricity consumption by EVs in comparison to the overall electricity consumption is considerably low. That's why the electricity price is increased less than 4% in all the areas as the result of implementation of LCFS and consequently the size of EVs.

The electricity price changes are dependent on both the demand and supply. As the supply function of the electricity is a step function, an increase in demand can increase the electricity price or may also keep it level, as can be seen in above figures. In this thesis, the generators can split their bids to different prices and to reduce the risk of not being cleared. The electricity price can remain unchanged by increasing the demand while the same marginal generation unit at the same price bidding level is serving the increased demand. The banking strategy also has low impact on the number of EVs and consequently on electricity price change, as shown in Figure 35.

The unbundling in the electricity market has made it impossible that the same entity to provide both generation services and retailing, EV aggregation and LCFS. This has been reflected in the developed EMMEV model in this thesis. Without unbundling, the market players will have market power and have negative social affects [111].

In the model, the renewable generation units have priority for dispatching due to involvement in feed-in-tariffs (FiT) which is called merit of order [112]. The renewable generation is remunerated with FiT their presence on the market is equivalent to offer of a certain quantity at a zero price.

This moves the global offer curve to right and the intersection with the demand curve takes place at a lower price market. Therefore, it is observed that this makes the electricity market price lower.

### 5.1.2 Sensitivity Analysis

A large amount of sensitivity analysis is done to understand the dependency of different parameters on EV penetration till 2030 and electricity price changes. The slope of the change for EV penetration and electricity price related to each parameter determines the sensitivity level.

- Neutral: means a change in that parameter doesn't change the electricity price and EV penetration.
- Low: means a change in that parameter changes the electricity price and keeps EV penetration relatively low.
- High: means a change in that parameter changes the electricity price and keeps EV penetration relatively high.

The sensitivity of all of the parameters shown in Figure 29 are described in Table 25. As shown in the above table, the penetration of EVs in 2030 is highly dependent on total number of the LDV and the share of each type of vehicle in the whole fleet of vehicles. On the other hand, the electricity market price is highly dependent on general electricity consumption, power generation and share of EV in the system.

The results are the outcome of numerous simulations of the model which are summarized in the table and described in the paragraphs below.

As shown in the table, the number of countries in the electricity market has no influence in electricity price and EV penetration by end of 2030. The test system has been divided 3 countries (instead of current 2) and the it is shown that the electricity price and penetration has no influence on the electricity price and penetration of EVs. This is due to the fact that the increase number of countries, the generation assets can serve the load in a similar manner as before and such a change cannot affect the electricity price and number of EVs. It is clear, if the market condition and generation assets change with a change of number of countries, it is of course expected that the number of EVs and electricity price can change.

The population has one of the highest influences on the electricity price and penetration of EVs in 2030. This is due to electrification is increasing as a result of trend towards decarbonization. The population in the model is expected to increase in EMMEV by 1% per year. In order to show this, the model is run by keeping all the parameters fixed and then changing the population. Based on the model, the higher the population, the higher the number of vehicles in total and the higher electricity consumption. The higher electricity consumption naturally leads to higher electricity price. This is due to the fact that the long-term planning for investment in the grid has not been considered in this thesis. The congestion, as described in section 3.8, is managed by zonal pricing. Therefore, it is potentially possible with an appropriate long-term grid planning and proper asset management [113] (which all the utilities are doing), the increase in electricity price (caused by increase in the population and consequently increase of electricity consumption) can be controlled.

The penetration of EVs in 2030 can be highly influenced by population increase. As in the EMMEV, the higher number of vehicles would lead to higher number of vehicles which leads to higher number of LCFS certificates to be issued. The revenue from the certificates go to the investment for the EV charging stations which would naturally increase the new issued LCFS (due to increase of low-carbon fuel consumption by EVs) and would increase the number of EVs.

**Table 25**: **Sensitivity of variables**

| Parameter | Number of countries in the electricity market | Population in each country | Electricity consumption per person | Power generation capacity | Number of LDV per person |
|---|---|---|---|---|---|
| Sensitivity of EV penetration in 2030 in relation to | Neutral | High | Neutral | Low | High |
| Sensitivity of electricity price in relation to | Neutral | High | High | High | Low |

The other parameter which is used to run a sensitivity analysis is electricity consumption per person. Keeping all other parameters fixed, the model is run with different levels of electricity consumption per person. The results show that the amount of electricity consumption per person has a large influence on the electricity price, naturally. On the other hand, the electricity consumption per person has no influence on EV penetration in 2030.

The power generation capacity low influence on the EV penetration and high influence on the electricity price. Once more, the model is run by keeping the all the parameters fixed and changing the power generation capacity of selected power plants. The capacity of the power plants changes the electricity price, but it has small influence on the EV penetration.

Finally, the number of LDV per person is selected as the other measure to calculate flexibility. Like before, the other parameters are kept fixed and the number of LDV per person is changed to see how the electricity price and penetration of EVs can be changed. The higher the number of LDV per person, the higher electricity price and penetration of EVs. However, the penetration of EVs is more influenced by the change of number of LDV per person than electricity price.

The regulators in LCFS set a maximum price for credits each year. This price will increase this year based on inflation and other economic parameters [40]. As shown in Figure 36, the initial percentage of EVs in each area is between 1-2% and the total EV penetration is 1.58%. In Figure 36, the sensitivity of final percentage of EVs against 0 to 5.5% of change of credit prices is depicted.

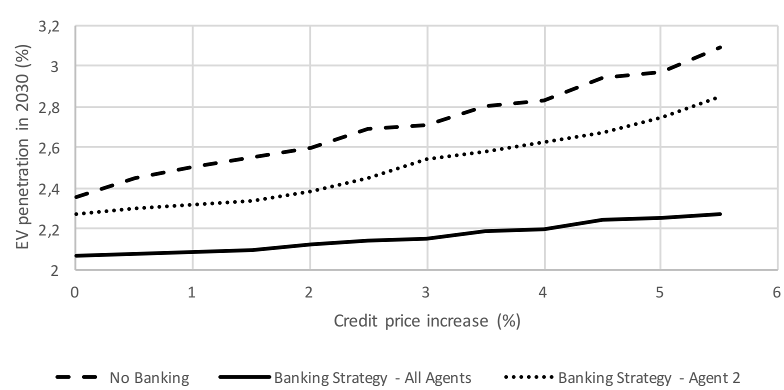



**Figure 36: Impact of LCFS credit prices on EV penetration**

In the LCFS market, the agents mainly trade their credits in Ongoing LCFS Credit Market which is a forward market with bilateral agreements. However, the Credit Clearance Market happens rarely and if that happens more frequently, it will help the price competitiveness and eventually more benefits from a banking strategy. In EMMEV, the agents only trade in LCFS Credit Market and the prices increase per year by a percentage determined by the model. As a next step in modeling, the Credit Clearance Market can be modeled. Regulated entities can buy LCFS credits in the bilateral market (Credit Clearance Market) intended to supply cost-controlled credits in the event of a market shortage.

## 5.2 Summary and Discussion

The future of energy systems is where the transportation is more interconnected to energy systems [29]. The LCFS is a policy with the aim of promoting low-carbon fuels. In this thesis, an agent-based model called EMMEV is developed to investigate the influence of the LCFS on the number of EVs and on electricity price.

The effectiveness of this policy is mainly dependent on wide geographical spread (on national level at least), resilience of market liquidity (availability of the enough credit to make a liquid market. This is mainly needs to be set by the regulators), and price competitiveness. The effectiveness of the LCFS will not be that high if the countries had less population, or fewer regions and countries were involved in the model. Showing the effectiveness of the policy is part of the reason that two countries and two price regions in each country are considered in the model. Based on the assumption that agents reinvest the revenue from the LCFS on EV charging infrastructure or other EV-promoting activities such as incentives, the effect of the LCFS on the adoption of low-carbon vehicles is quite small, as demonstrated in this thesis. Consequently, the impact of an increased number of EVs on electricity prices is not considerable.

In EMMEV, it is assumed that the agents only trade in the Ongoing Market, since the regulated parties have contracts in the ongoing LCFS Credit Market, and there are no credit shortfalls. It is also assumed an elasticity of each additional normal charging station per 100,000 residents would increase its EV market share by 0.12% and the profits from the LCFS are spent in charging infrastructure (although other studies have shown that rebates might be more effective [114]). The results from EMMEV show that the impact of the LCFS on EV penetration is low. It is also indicated that the LCFS is not an effective driver for EV penetration in a small geographical area with low liquidity shown in [41]. The LCFS seems to need large regulated parties to guarantee the resiliency required for market liquidity, since supply and demand are dependent on a larger number of participants.

Market liquidity is one of the important factors for financial stability and real trade activity in the LCFS. Low market liquidity downgrades the efficiency of the market [115], but is also the result of inefficient design of the market. The regulators should follow the market changes every year to target a right level and adapt the supply and demand of credits to ensure trade activities in the market.

In case of low market liquidity, the LCFS will be fragile and likely to evaporate in response to shocks. As described above, LCFS can be effective when the market is spread in wide geographical areas to ensure enough credits in the market. The credit prices may also become less unpredictable in case of higher market liquidity. Highly uncertain prices will decrease participation of fuel distributors in the market and will make it hard for investors to make long-term decisions. In EMMEV, the price is set in ongoing market which can give a somewhat higher certainty on the price.

The price competitiveness in the LCFS is dependent on more regular Credit Clearing Markets. Bilateral contracts will not give enough confidence to investors to be ensured that they can sell their credits and have credible predictions of the credit price. On the other hand, those agents who have not met their previous year-end obligation can use Credit Clearing Markets to provide additional compliance flexibility. The results from this thesis show that the banking strategy of the agents contributing to the LCFS can have a small negative impact on penetration of EVs, unless there is regular Credit Clearance.

From the electricity market perspective, the initial influence of EVs penetration on electricity prices is low. The electricity price in both the banking and no-banking case did change, but very marginally.

Even in case of higher EV penetration, the influence on electricity price is not considerable. There are other studies which they might show considerable change in the electricity price as result of EV charging [49]. The influence on the electricity price is highly dependent on the charging strategy (ToU, Smart or dumb), battery size and the charging power. In this thesis, the battery size is relatively low and the power to charge the EVs is also relatively low. Therefore, these assumptions for EV charging power and battery size defines the size of impact from EV charging on the electricity price.

As with many policies, the design and context of implementation of the LCFS will have an influence on its performance. It has been shown, in a simplistic model (considering all the complexity that it is hard to be put in a model) as in this thesis, that in a small market without credit clearance, some agents might bank their credits, leading to a lower EV penetration rate than what could otherwise be expected.

# Chapter 6
# Optimal Management of Battery Charging of Electric Vehicles with Micro Grids

In the last chapters, the upstream electricity market and transportation polices were addressed. This chapter addresses the downstream challenges in the integration of EVs to the power grid. Micro Grid is introduced as a way to manage the load from Electric Vehicles.

Unlike the other chapters, in this chapter a 'Micro Grid' test system is introduced and used for testing. The test system for this chapter is completely different from the other chapters. This is due to the fact that the introduced approach of optimizing EVs charging power in the grid to be tested in a smaller system. The main focus is to test the functionality of the approach (called OPSC) and obviously, this charging system can be expanded to be used for the bigger systems as well (which is not the main focus of this thesis).

## 6.1 The MG architecture with EVs

A MG is an LV distribution system with several comprising small modular generation units connected to the LV network through power electronic interfaces, electrical loads, storage devices and a hierarchical control and management system supported by a suitable communication infrastructure, such that the MG can be operated either in islanded mode or connected to the MV system [9] [116]. The MG is centrally controlled and managed by the MGCC (Micro Grid Central Controller) installed at the MV/LV secondary substation, which is responsible to head the MG hierarchical control system. For this purpose, the MGCC includes several key functions that support adequate technical and economic management policies and allow for the providing of set points to the second control level comprising Micro Grid Controllers (MC) and Load Controllers (LC), in order to control locally the controllable microgeneration units and the responsive loads, respectively.

Regarding the MG concept, the single-phase electrical batteries belonging to the EV have been included through a smart power electronic interface with a specific control approach, called the Vehicle Controller (VC) [57]. Thus, the MG architecture with EV connected to it is represented in Figure 37.

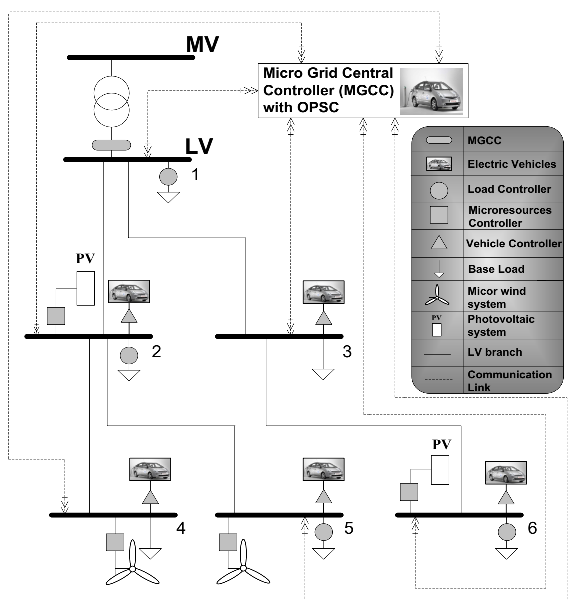



**Figure 37: The MG architecture with EVs**

In order to assure a smart management of battery charging of EVs, a new feature was included on MGCC - an Optimal Power Set-point Calculator (OPSC). The OPSC is then responsible to calculate the rated charging power of each EV battery to be sent from the MGCC to the corresponding VC. For this purpose, when each EV is plugged in, the corresponding VC sends to the MGCC the following information: a) the battery capacity and technology, b) the battery initial state of charge, c) the expected EV parking duration and d) the battery desired final state of charge. Based on this information and considering the forecasted local and daily load diagram as well as the forecasted local daily production from microgeneration systems, the Optimal Power Set-point Calculator (OPSC) uses an Evolutionary Particle-Swarm Optimization (EPSO)-based optimization procedure to find the best hourly battery charging rates for the 24 hours.

## 6.2 The OPSC optimization problem

For a given LV distribution network, beyond the data sent by VC to the MGCC, described in the previous section, the initial data of the OPSC optimization problem includes also the area mobility pattern given by the expected number of EVs that will plug-in in each hour according to the human behavior of the corresponding area. The solution of the hourly active power set points corresponding to the individual charging rates of EVs can be obtained by solving an optimization problem that involves the minimization of the variance of the active power flow through the MV/LV substation considering the additional consumption of the EV batteries. This has been first introduced in [52] and was adopted in this work aiming to improve the system operating conditions through the EV additional load transfer from the peak hours to the valley hours and to the periods corresponding to high local generation levels. Mathematically, the problem can be formulated as:

$$\min\left(\sum_{h=1}^{24}\frac{(P_h-\mu)^2}{24}\right) \qquad \text{Equation 5}$$

where $P_h$ is hourly injected active power considering the EVs consumption and μ is the average value of active power after adding EVs consumption at bus 1 depicted in Figure 40, which are derived as in equation 6 and 7, respectively.

$$P_h = P_{h,MG} - P_{h,base} - P_{h,PHEV} - P_{h,loss} \qquad \text{Equation 6}$$

$$Q_h = Q_{h,MG} - Q_{h,base} - Q_{h,PHEV} - Q_{h,CAP} \qquad \text{Equation 7}$$

$P_{loss}$ is the active power losses and $Q_{CAP}$ is the reactive power injected by capacitor banks.

$$\mu = \frac{\sum_{h=1}^{24} P_h}{24} \qquad \text{Equation 8}$$

In equation 6 and 7, $P_{h,MG}$, $P_{h,base}$, $Q_{h,MG}$ and $Q_{h,base}$ are active and reactive power, the base regular load diagram and the microgeneration levels during 24 hours of a typical day. The following are the equality constraints for load flow:

$$P_i(V,\delta) - P_{gi} + P_{di} = 0 \qquad P_{di} = P_{base\ i} + P_{EV\ i} \qquad \text{Equation 9}$$

$$Q_i(V,\delta) - Q_{gi} + Q_{di} = 0 \qquad \text{Equation 10}$$

In the above equations, $P_{di}$ is active power demand at each busbar (i) and $Q_{di}$ is reactive power demand at each busbar. $P_{gi}$ is active power generation at each busbar and $Q_{gi}$ is reactive power generation by capacitor bank at each busbar.

The constraints are for the each busbar. V represents the voltage value and $\delta$ is the angle in each busbar. The objective function given by equation 4 is subjected to the following technical constraints:

$$\mathrm{V_{min}} < \mathrm{V_i} < \mathrm{V_{max}} \qquad \mathrm{i} = 1 \dots \mathrm{n} \qquad \text{Equation 11}$$

$$LFSOC_j < OFSOC_j < HFSOC_j \qquad j = 1 \dots p \qquad \text{Equation 12}$$

$$\mathrm{I_k} < \mathrm{I_{k\,max}} \qquad \mathrm{k} = 1 \dots l \qquad \text{Equation 13}$$

$$\mathrm{P_{MG\,min}} < \mathrm{P_{MG\,i}} < \mathrm{P_{MG\,max}} \qquad \mathrm{i} = 1 \dots \mathrm{n} \qquad \text{Equation 14}$$

$$\mathrm{Q_{MG\,min}} < \mathrm{Q_{MG\,i}} < \mathrm{Q_{MG\,max}} \qquad \mathrm{i} = 1 \dots \mathrm{n} \qquad \text{Equation 15}$$

Indicators i and j shows the order of each bus bars and the order of each EV, respectively, being n the number of buses and $p$ the number of plugged-in EVs. $V_i$ shows the voltage in each bus bar and $V_{min}$ and $V_{max}$ represent, respectively, its minimum and maximum values (0.9 and 1.1 p.u). The voltage is controlled by reactive power. As part of load flow, it is assumed in this model that there enough reactive power to compensate for the voltage regulation in the bus bars. The reactive power in the model is injected by capacitors.

LFSOC, HFSOC and OFSOC shows the lowest-desired, highest-desired and optimal state of charge of the battery while the first and second are input values stated by the car driver and the last value is the output of the optimization problem. Finally, $I_k$ and $I_k$ max are the current in line *k* and the corresponding maximum limit, respectively, being *l* the number of lines in the network.

$$Q_{CAP\ min} < Q_{CAP\ m} < Q_{CAP\ max} \qquad m = 1 \dots capm \qquad \text{Equation 16}$$

Indicator *m* is related to each capacitor and *capm* is the total number of capacitors.

## 6.3 Using EPSO to implement the OPSC

EPSO was adopted to find good solutions for the optimization problems. This tool is a powerful optimization metaheuristic particularly well suited to deal with combinatorial problems with a large number of possible solutions, like this one, where discrete variables (power set-points change by 0.01 kW steps) are used [117]. However, the adoption of this procedure demands the following main stages:

- A suitable codification of each potential solution – the definition of the particle object parameters;
- The definition of a suitable fitness function in order to represent the quality of each solution, expressed in terms of the load curve variance;
- The use of the EPSO procedure.

### 6.3.1 Particle definition

EPSO is a population-based optimization algorithm. At a given generation, the set of potential solutions for the problem to be solved is called a set of particles or swarm. Each particle comprises two sets of parameters, the strategy parameters and the object parameters, corresponding respectively to the weights that govern the movement rule and to the particle position into the search space. Since EPSO is a self-adaptive method, benefiting from the evolutionary process to progressively adapt the parameters that guide its own search, the particle definition involves only the specification of the object parameters [118].

Under the framework of the OPSC optimization problem to be solved, the potential solutions involve the active power set-points for each EV at each hour, corresponding to hourly charging rates for each battery, as stated before. Therefore, the size of set of object parameters is $p \times 24$, where p is the number of EVs. Figure 38 shows the structure of the object parameters of the particle.

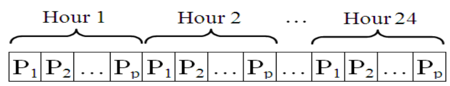



**Figure 38: Structure of the particle object parameters**

The discrete values in EPSO are shown in 0.01 kW steps. This means that the power in each hour would increase or decrease to reach to an optimal value in 0.01 kW steps. EPSO is an evolutionary meta-heuristic that implements a scheme of self-adaptive recombination, borrowing the movement rule from PSO (Particle Swarm Optimization). This is the reason that 0.01 kW steps selected to use EPSO self-adaptive capability to reach to a final optimal point.

### 6.3.2 Evaluation function

The problem of minimizing the objective function described by equation 17, when subjected to the constrains identified, can be treated in terms of fitness function as

$$FIT = \sum_{h=1}^{24} \frac{(P_h - \mu)^2}{24} + P + V \qquad \text{Equation 17}$$

The term P represents the particle penalty when the required state of charge of the batteries is not achieved. The term V refers to a penalty when the voltage in at least a busbar is not within the permitted voltage levels. These two penalties are described in the following equations.

$$P = P_1 + P_2 = \left(\sum_{j=1}^{p} P_{1j} + \sum_{j=1}^{p} P_{2j}\right) \times 10^5 \qquad \text{Equation 18}$$

$$V = V_1 + V_2 = \left(\sum_{j=1}^{p} V_{1j} + \sum_{j=1}^{p} V_{2j}\right) \times 10^5 \qquad \text{Equation 19}$$

In the above equations, P is calculated for each PHEV and V is calculated at each busbar as described in the below equations.

$$P_{1j} = \begin{cases} (OFSOC_j - HFSOC_j) \times BC_j & OFSOC_j > HFSOC_j \\ 0 & else \end{cases} \qquad \text{Equation 20}$$

$$P_{2j} = \begin{cases} (LFSOC_j - OFSOC_j) \times BC_j & OFSOC_j < LFSOC_j \\ 0 & esle \end{cases} \qquad \text{Equation 21}$$

The above equations shows how a particle is penalized for keeping the charging within SOC of the battery. Penalizing the particle due to voltage constraint in each busbar is shown in the following equation.

$$V_{1i} = \begin{cases} (V_i - 1.1) & V_i > 1.1\, p.u. \\ 0 & else \end{cases}$$ Equation 22

$$V_{2i} = \begin{cases} (0.9 - V_i) \times BC_j & V_i < 0.9\, p.u. \\ 0 & esle \end{cases}$$ Equation 23

The index j accounts for the EV number, index *i* is for each busbar and BC is the battery capacity. The technical constrains regarding thermal limits of branches are only considered in the load follow in the next stages.

### 6.3.3 The EPSO based optimization procedure

The approach starts with the search space definition through the specification of both the minimum and maximum values of each object parameter of the particle. For this purpose, it was assumed that the minimum values of the active power set-points are set to zero, meaning that although the EVs are plugged in, their batteries are not in charging mode. Regarding the maximum values of the active power set-points, it was assumed that they correspond to the maximum charging rate of the EV batteries, meaning that when no technical constrains arise concerning the grid operation, the EV batteries will charge according to its nominal charging rate.

After defining the search space, it is expected that the EPSO algorithm will find the best solution or, at least, a good solution in the sense of the fitness function. For this purpose, the usual EPSO operators (replication, mutation and selection) are used and the following sequence of steps has to be carried out for each particle in the swarm [119]:

- Perform replication;
- Perform mutation of the particle strategy parameters;
- Perform recombination according to the movement rule;
- Perform the evaluation function;
- Perform selection.

In this work an EPSO algorithm was used with 20 particles in the swarm, replication factor r =1 (each parent gives birth to one descendant) and Gaussian mutation with learning rate $\tau$=0.5. The stopping criterion is the maximum number of iterations, which was assumed to be 1500. These parameter values were adopted based on the experience in using EPSO to deal with this problem.

After performing the EPSO algorithm, the best particle to be found, which corresponds to the lowest value of the fitness function, should respect the technical constrains regarding the voltage profile of each bus and the thermal limits of LV branches. Thus, in order to check these technical constraints, an unbalanced three-phase load flow tool [120] was used. In case of these constraints are not verified, due to branches' congestion problems or bus voltage profiles being too low, the upper limits of the search space are decreased and the EPSO algorithm will be run again. The approach algorithm is shown graphically by means of the flow chart depicted in Figure 39.

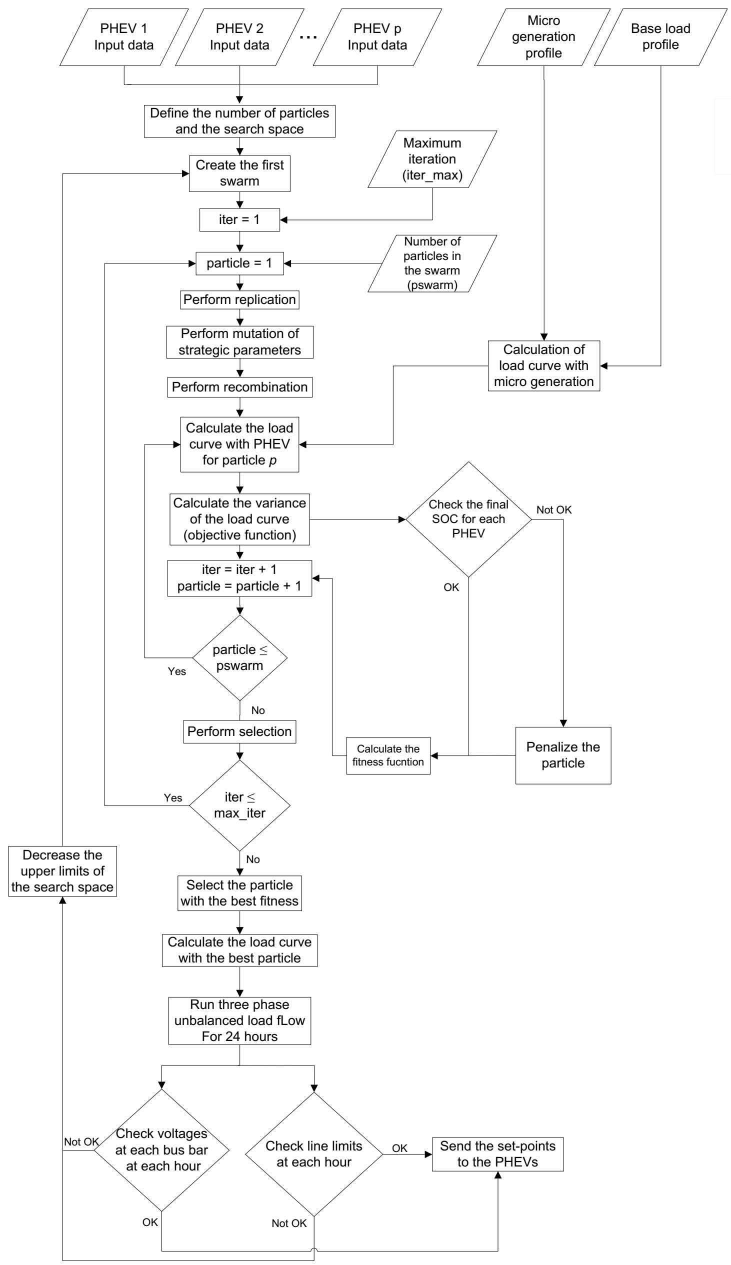



**Figure 39: The EPSO based OPSC approach**

The final set-point is OFSOC which described in the equations above ad it is the main output of the model. The figures in the next sections will show different load curves with OFSOC for all PHEVs.

#### 6.3.3.1 Why EPSO?

Evolutionary Particle Swarm Optimization (EPSO) is a combinatorial optimization tool which inspired in both evolutionary algorithms and in particle swarm optimization algorithms [121]. The tool is designed for very complex problems with discontinuity of control variables. The main reason why this tool is selected for this thesis is to prepare a platform for future development of even more complex problems with reactive capacitor banks and more discontinuous values. The future work has been described in Section 7.1 of this thesis.

## 6.4 Small Test System for testing OPSC in a MG

In order to assess the performance of the approach described above, the 24-bus bar LV distribution network presented in Figure 40 was used. It corresponds to a typical rural, 400 V grid, fed by a 50 kVA upstream transformer. This is a fairly weak residential network, comprising mainly single-phase loads. However, a few three-phase loads are also connected to this network. Such a power system with unbalanced loads consisting of single-phase and three-phase loads represents reality of power systems much more than a balanced single-phase power system. In this test system, it was assumed that there are microgeneration systems, both wind and Photovoltaic (PV).

Due to the common lack of typical LV network full characterization, it was assumed that the individual base loads are homothetic, being thus obtained from the LV network typical base load diagram presented in Figure 41, according to the corresponding contracted power and taking into account a suitable LV network simultaneity factor for the peak hour. It should also be noted that the single-phase loads were distributed among the different phases trying to minimize the load unbalance.

It was also assumed that the microgeneration systems, both wind and PV, are only connected to the load buses. Taking into account that all the micro wind and PV systems are subjected to the same wind and solar conditions, respectively, they follow the same generation profiles. For a typical summer day, both wind and PV profiles are presented in Figure 42 in terms of the percentages of the corresponding installed capacities.

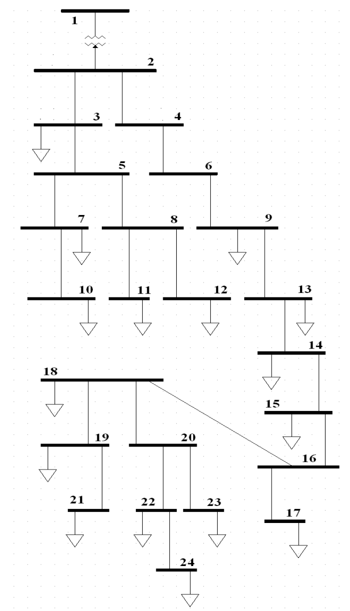



**Figure 40: The 24-bus bar LV distribution network**

In order to perform a 24-hour simulation, a typical daily load diagram was used, as depicted in Figure 41, corresponding to a typical summer day.

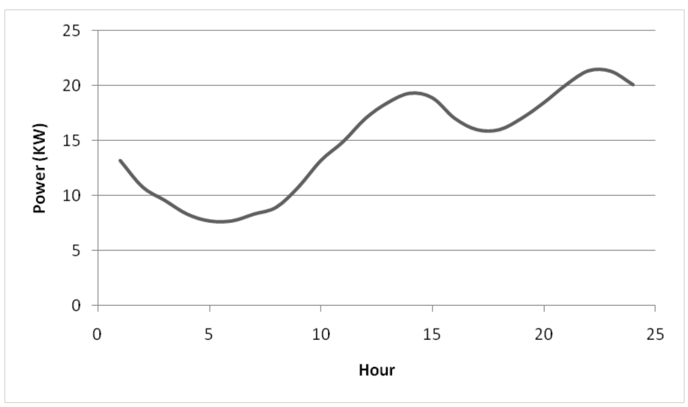



**Figure 41: The load diagram during a typical summer day**

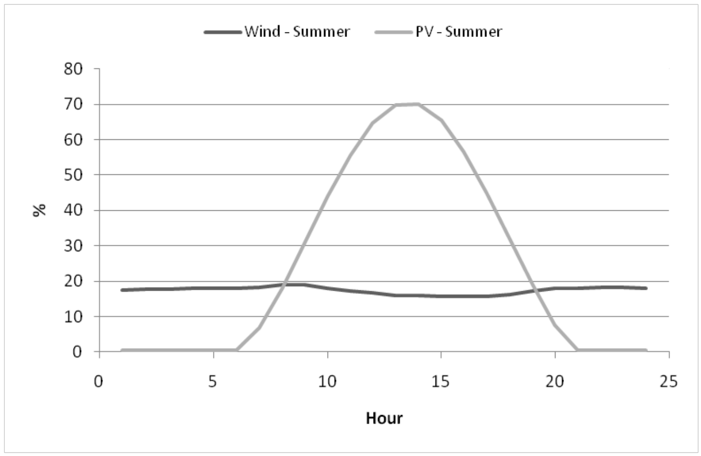



**Figure 42: Microgeneration profiles (percentage of the installed capacity)**

The installed capacities of both micro wind and PV systems were determined based on the following assumptions:

- The total installed capacity of the LV network is less than a quarter of the upstream transformer rating (in this case less than 12,5 kW);
- For each load bus, the installed capacity of microgeneration systems is one half of the corresponding contracted power, being always less than 3 kW;
- The share of the installed capacity is 80% for PV systems and 20% for micro wind systems.

In order to fully describe the adopted test system, it is necessary to determine the number of EVs, which is usually estimated as a percentage of the total number of cars in the area. For this purpose, it was assumed that the LV network presented in Figure 40 provides electricity for 50 people and in average each 3 people have 2 cars in that area. Based on these assumptions and using the methodology presented in [52], it was estimated that 16% of the ICE-based cars will convert to EVs, meaning that 8 EVs will plug-in in this LV network. However, this is a future scenario corresponding to the year 2022. Therefore, the base load diagram presented in Figure 41 was updated in order to include the yearly rate of load increase. For this purpose, it was assumed a 0.5% of yearly load increasing.

The EVs are connected to the several bus bars and in different phases as described in Table 26.

**Table 26 Connection of EVs to the grid**

| EV no. | Bus bar | 1 or 3 phase | Phase |
|---|---|---|---|
| 1 | 3 | 1 | 1 |
| 2 | 7 | 1 | 2 |
| 3 | 9 | 1 | 3 |
| 4 | 10 | 1 | 1 |
| 5 | 11 | 1 | 3 |
| 6 | 11 | 1 | 1 |
| 7 | 12 | 3 | - |
| 8 | 13 | 3 | - |

Since the base load connected to bus 12 and bus 13 is a three-phase load it was assumed a three-phase connection regarding EV 7 and EV 8. This EV distribution follows a connection strategy corresponding to the best-case scenario from the grid operation perspective. This is due to the fact that the EVs are connected to the bus bars nearest the upstream transformer, meaning that better voltage profiles are expected as well as lower levels of branches' congestions. The worst-case scenario corresponds to a situation where the EVs are connected to bus bars located farthest from the transformer. However, this case scenario was not investigated in this study.

## 6.5 Simulation Results and Discussions

The developed approach has been tested using the test system presented, considering the EVs specifications presented in Table 27.

The considered EV fleet includes cars with different rated power according to the battery capacity [122] intended to face different owners needs in terms of driving ranges. The average charging time of each EV was assumed to be 4 hours at their rated power. Regarding the starting time specified in Table 27, it was assumed that EV owners plug in their cars when they arrive from the last journey, using domestic charging points.

**Table 27 Detailed information about EVs**

| EV no. | Battery capacity (kWh) | Charging power (kW) | Starting time | Parking Duration | State of Charge (%) | | |
|---|---|---|---|---|---|---|---|
| | | | | | ***Primary*** | ***Min final*** | ***Max final*** |
| 1 | 8 | 2 | 17:00 | 8 | 10 | 70 | 100 |
| 2 | 8 | 2 | 17:00 | 8 | 10 | 70 | 100 |
| 3 | 8 | 2 | 18:00 | 12 | 10 | 70 | 100 |
| 4 | 8 | 2 | 19:00 | 12 | 10 | 70 | 100 |
| 5 | 10 | 2,5 | 20:00 | 10 | 15 | 75 | 100 |
| 6 | 10 | 2,5 | 20:00 | 11 | 15 | 75 | 100 |
| 7 | 15 | 3 | 20:00 | 24 | 20 | 80 | 100 |
| 8 | 15 | 3 | 22:00 | 24 | 20 | 80 | 100 |

When the EVs are connected to charge their batteries, the car driver provides information about the parking duration in order to allow the management of the battery charging according to the specified final state of charge and taking into account the initial state of charge. So this data is also included in Table 27.

In order to demonstrate the performance of OPSC approach, four case studies were planned, as summarized in Table 28, aiming to compare the effects on the system operation resulting from using the OPSC based smart charging strategy and a dumb charging strategy. These effects were also compared considering the LV network with microgeneration and without microgeneration.

**Table 28: Case studies**

| Case study | Microgeneration | Smart / Dumb charging |
|---|---|---|
| A | No | Dumb |
| B | Yes | Dumb |
| C | No | Smart |
| D | Yes | Smart |

It should be noted that when a dumb charging approach is used, EV owners are completely free to connect and charge their vehicles after parking without any kind of charging control. The charging starts automatically when EVs plug in and lasts for the next four hours (assumed in the model) with the charging rate specified in Table 27.

### 6.5.1 Dumb charging results without microgeneration

Since all the EV owners charge their vehicles when they arrive home from the last journey of the day, this procedure provokes an increase in load consumption that lasts for four hours, as can be observed from Figure 43.

Moreover, the high consumption of EVs happens at peak hours (in the evening), leading to a considerable increase in the total peak power. The additional load of EVs, in this weak rural LV network, brings some grid operation problems, such as branches’ congestions and large voltage drops. Problems of convergence were verified when performing the 24-hour load flow analysis during the peak hours. This fact stresses the need to either reinforce the grid infrastructures or adopt a smart charging strategy in order to transfer the EVs load from the peak hours to the valley hours.

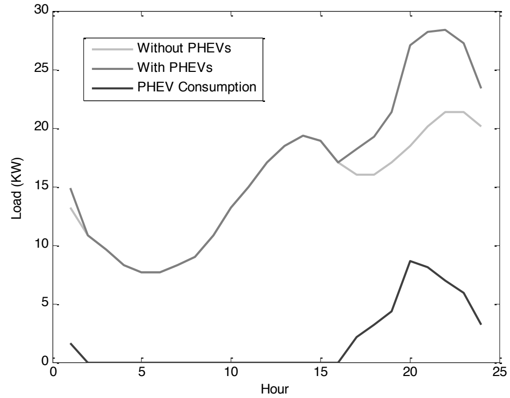



**Figure 43: LV grid load diagram for dumb charging without microgeneration**

### 6.5.2 Dumb charging results with microgeneration

Considering the availability of microgeneration systems, both wind and PV, with the corresponding generation profiles presented in Figure 42, the resulting LV grid load diagram is presented in Figure 41.

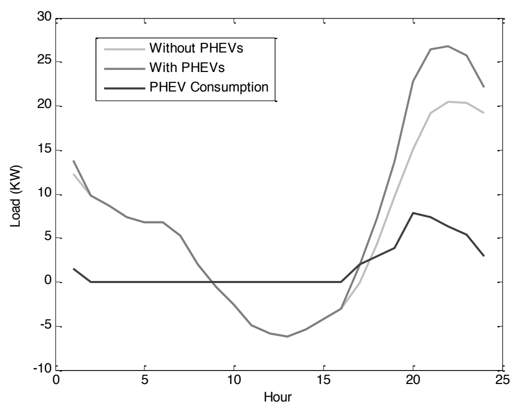



**Figure 44: LV grid load diagram for dumb charging with microgeneration**

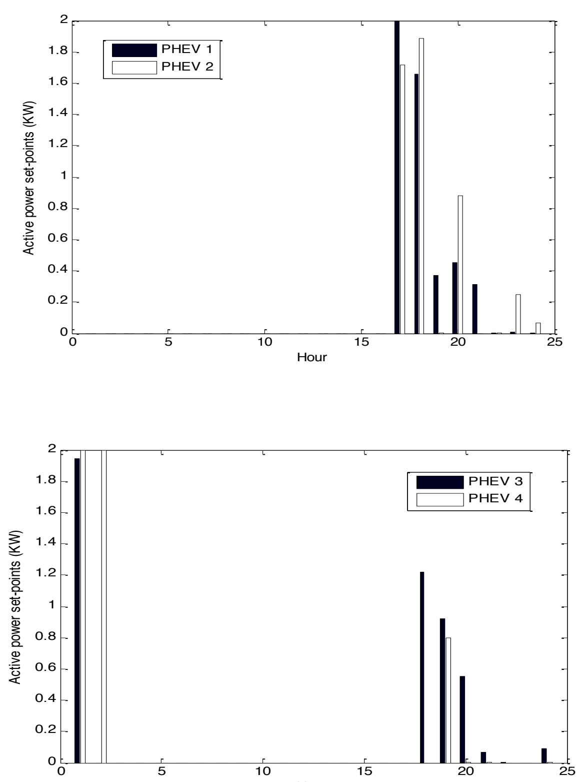
As can be observed from Figure 44, the local generation provided by both micro wind and PV systems does not affect significantly the load diagram during the peak hours, and a similar peak power increase was verified when comparing Figure 44 with Figure 43.

During the period corresponding to the PV systems generation, as the EV consumption is zero, the LV network is exporting power to the upstream MV network. Therefore, it will be interesting to move the additional EV load from the peak hours to this period, if EVs are parked, exploiting the OPSC-based smart charging strategy.

### 6.5.3 Smart charging without microgeneration

The OPSC-based smart charging strategy was applied to find suitable active power set-points in order to manage the charging process of the EV batteries, according to both the parking duration and minimum final state of charge, which are specified in Table 27, trying to minimize the negative impacts regarding the network operating conditions. For this purpose, the search space was defined, as already mentioned previously, with the lower limits set to zero and the upper limits set to the charging rates of each EV battery described in Table 28. It should be noted that the set of the particle object parameters comprises 192 active power set-points and the required computation time was around 200 seconds.

Considering the LV test system without microgeneration and after performing the EPSO-based OPSC approach, the obtained hourly active power set-points corresponding to the battery charging rates are presented in Figure 45.



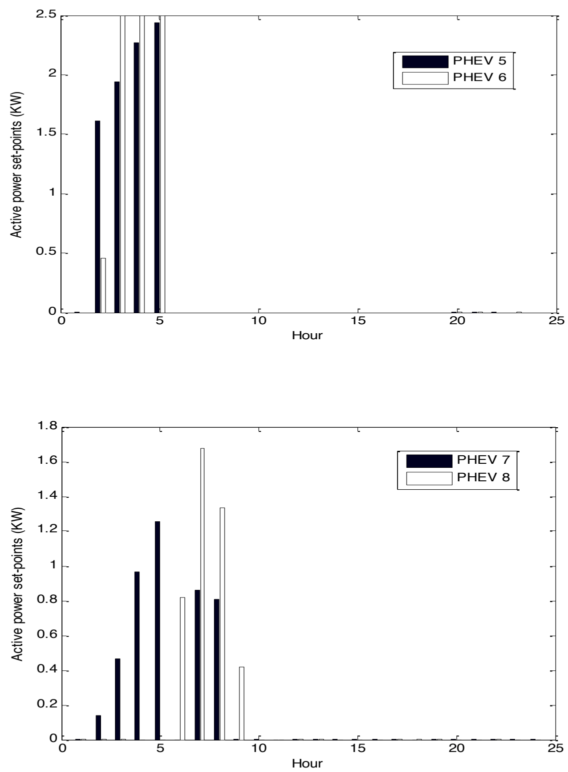



**Figure 45: Hourly active power set-points for each EV**

As can be observed from Figure 45, all the EVs charge their batteries with an hourly variable charging rate. However, the minimum state of charge specified by the EVs owners was achieved for all the cars without grid operation problems.

Regarding EVs number 1 and 2, although they are parked between 17:00 and 23:00, they are almost charged before 20:00 in order to avoid additional load during the peak hours. In case of EV 3 the battery load is partially transferred to the valley hours. On the other hand, as the remaining EVs are parked during the night, their batteries are fully charged during the valley hours. It should also be noted that the batteries of EVs number 5 and 6 are charged later than those of EVs 7 and 8. This is since, in the last case, the charging duration was extended. However, although these two EVs can be charged freely for 24 hours, the preferred period relies on the valley hours.

As a result of the application of the OPSC-based smart charging strategy, the LV network daily load diagram was modified, as can be observed in Figure 46.

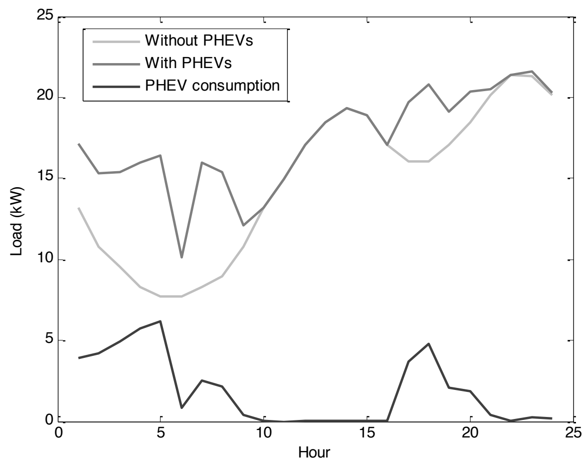


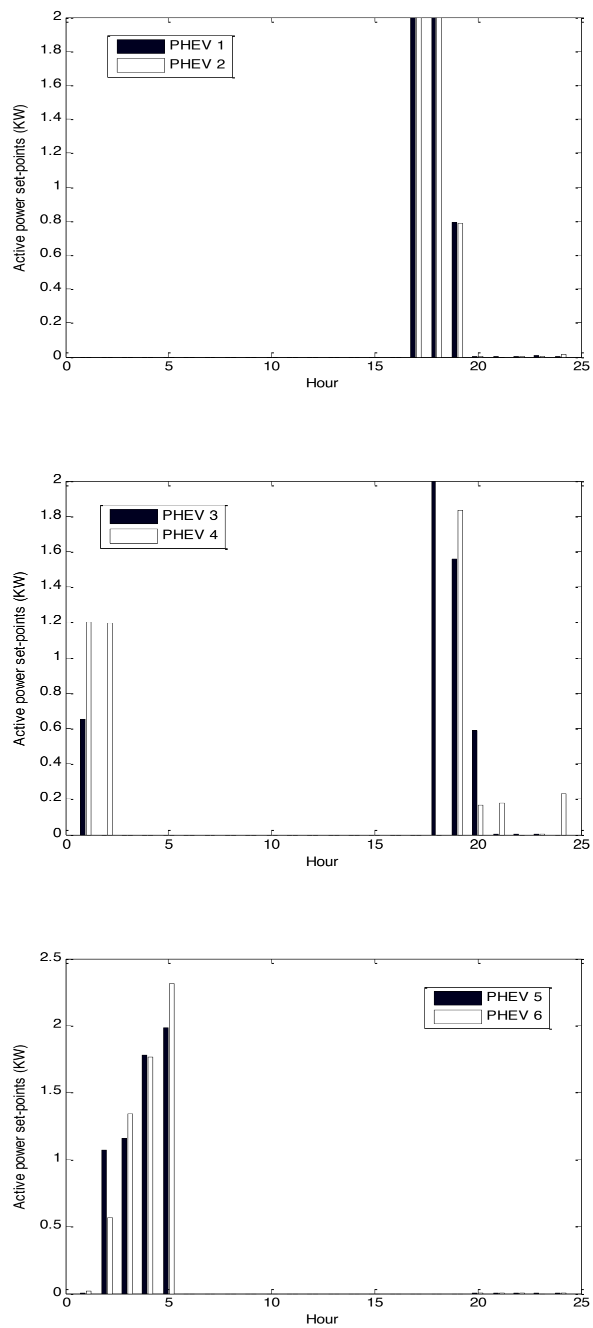

**Figure 46: LV grid load diagram for smart charging without microgeneration**

When compared with the load diagram presented in Figure 43, which corresponds to the dumb charging strategy, the load curve is flatter because an amount of the additional EV load was shifted from the peak hours to the valley hours.

### 6.5.4 Smart charging with microgeneration

In this case study it was considered the presence of microgeneration systems, both micro wind and PV systems, in the test system LV network. The proposed OPSC-based smart charging approach was then applied considering the specifications presented in Table 27 and the same conditions of case study C, regarding the search space definition and the particle size (the set of object parameters). The required computation time was around 200 seconds. The obtained hourly active power set points that define the battery charging rates are presented in Figure 47.

When compared with the results of case study C, in particular these ones presented in Figure 45, the battery load corresponding to EVs number 7 and 8 was transferred to the period when PV systems are generating active power, the generation peak being around noon, as can be observed from Figure 47.



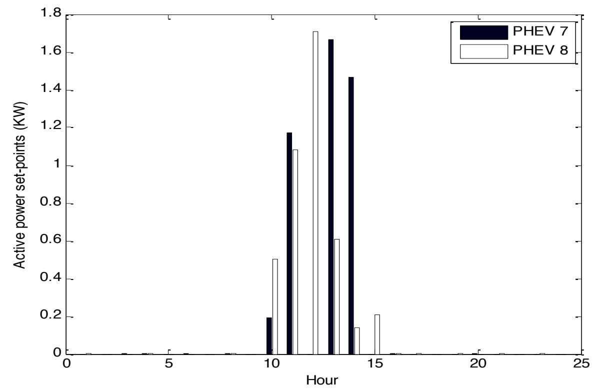



**Figure 47: Hourly active power set-points for each EV**

Following the EVs battery charging management based on the individual charging rates presented in Figure 47, the LV network daily load diagram was modified, as can be observed from Figure 48.

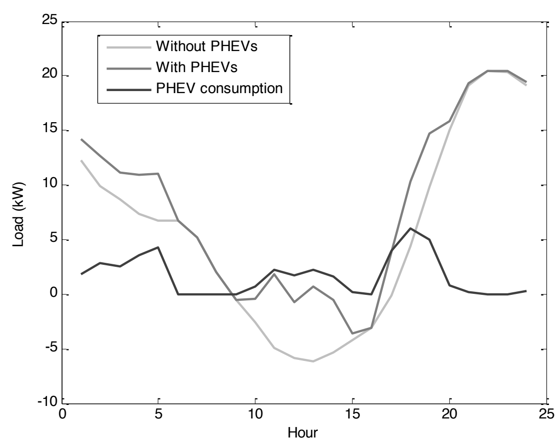



**Figure 48: LV grid load diagram for smart charging with microgeneration**

To conclude, large deployment of EVs will impose new challenges to power systems operation, to LV distribution networks, requiring thus the development of adequate technical management structures to deal with smart charging schemes in order to reduce the negative impacts of EV integration trying to avoid reinforcements in the grid infrastructures. In this context, an OPSC-based smart charging strategy was proposed in order to deal with EV battery management in LV networks, being this software module housed in the MGCC.

## 6.6 Summary and Discussion

The performance of the proposed approach was evaluated considering a typical LV distribution network integrating simultaneously microgeneration systems (wind and PV) and EVs. The results obtained point to the effectiveness and robustness of the developed approach to find hourly active power set points to charge each EV battery when EVs are parked. This charging scheme allows operating the LV networks in less stressed conditions.

The control of the local renewable generation can influence on the operations of the grid and also a Micro Grid. With increasing size of local generation units, the generated power can be locally controlled and to be directly fed to EVs. There will be a MGCC to manage the control of the aggregated load and generation under MGCC with higher voltage levels in the distribution grid.

A rule of thumb for the management of the EV charging is that the smarter the charging strategies, the lower cost for the operations and management of the assets in the distribution grid. The assets can be utilized in the most efficient way when smarter charging solutions is available in the grid.

Further developments include the enhancement and adaptation of the OPSC-based smart charging approach to deal with this problem in real time applications. The future development in the charging of the EVs is to control and design a fast charging or semi-fast charging solution within a microgrid.

# Chapter 7
# Conclusions and Future Work

The demand for road transport (both personal and commercial) is rising quickly with city expansions around the world. The electric vehicles (EVs) starting to challenge the power of internal combustion engine (ICE) cars by addressing air quality concerns [7] and the need to reduce carbon emissions [123]. This causes the increase of EVs in the cities due to support policies such as LCFS which is discussed in this thesis. The increased number of EVs makes changes both in the electricity market and now to operate the power grid.

From electricity market perspective, the price of electricity is increased (as shown in the models in the previous chapters). This increase in the prices should be managed by securing enough supply of electricity. The load from the transportation is now an important element in forecasting of the future load.

From power grid perspective, as discussed in this thesis, the grid needs to be managed in different ways. In this thesis, a Micro Grid structure is introduced and the management of load from EVs is being discussed. In this chapter of the thesis, the achieved results are presented and future work from this thesis is recommended.

## 7.1 Achieved Results

The LCFS is a policy with the aim to promote low-carbon fuels. In this thesis, an agent-based model called EMMEV is developed to investigate the influence of the LCFS on the number of EVs and electricity price. In addition, a feature in Micro Grid is being developed to manage the load from EVs. The following are the research questions of this PhD work. In this section, the answer to each research question is discussed.

1. How does LCFS policy increase the number of EVs?
2. How does the increased number of EVs influence the price of electricity?
3. What are the factors, including the ones from the electricity market, which make LCFS a more effective policy?
4. How do the technical constraints on a power system influence the charging of EVs?

Regarding the 1st and 3rd research question related to LCFS, the effectiveness of this policy is mainly dependent on wide geographical spread, resilience of market liquidity, and price competitiveness. Based on the assumption that agents reinvest the revenue from the LCFS on EV charging infrastructure or other EV-promoting activities such as incentives, the effect of the LCFS on the adoption of low-carbon vehicles is quite small, as demonstrated in this thesis. LCFS is not developed to incentivize the sales of EVs. Consequently, the impact of an increased number of EVs on electricity prices is not considerable.

In EMMEV, it is assumed that the agents only trade in the Ongoing Market since the regulated parties have contracts in the ongoing LCFS Credit Market and there are no credit shortfalls. It is also assumed an elasticity of each additional station per 100,000 residents would increase its EV market share by 0.12% and the profits from the LCFS are spent in charging infrastructure (although other studies have shown that rebates might be more effective [114]). The results from EMMEV show that the impact of the LCFS on EV penetration is low. It is also indicated that the LCFS is not an effective driver for EV penetration in a small geographical area with low liquidity. The LCFS seems to need large regulated parties to guarantee the resiliency required for market liquidity, since supply and demand are dependent on a larger number of participants.

The price competitiveness in the LCFS is dependent on more regular Credit Clearing Markets. Bilateral contracts will not give enough confidence to investors to be ensured that they can sell their credits and have credible predictions of the credit price. On the other hand, those agents who have not met their previous year-end obligation can use Credit Clearing Markets to provide additional compliance flexibility. The results from this thesis show that the banking strategy of the agents contributing to the LCFS can have a small negative impact on penetration of EVs, unless there is regular Credit Clearance. A regular Credit Clearance can neutralize the effect of banking by providing buyers and sellers with flexibility to negotiate mutually beneficial transactions.

As with many policies, the design and context of implementation of the LCFS will have an influence on its performance. We have shown, in a simplistic model, that in a small market without credit clearance some agents might bank their credits, leading to a lower EV penetration rate than what could otherwise be expected.

For the 2$^{nd}$ research question and from the electricity market perspective, the initial influence of EVs penetration on electricity prices is low. The electricity price in both the banking and no-banking case did change, but very marginally.

For the 4$^{th}$ research question and from Micro Grid perspective, large deployment of EVs will impose new challenges to LV distribution networks. Thus, the expansion of acceptable technical management structures to deal with smart charging schemes to eventually reduce the undesirable impacts of EVs integration (reinforcements in the grid infrastructures) is important. An OPSC based smart charging strategy was proposed to deal with EVs battery management in LV networks, being this software module housed in the Micro Grid Central Controller.

## 7.2 Future work

EMMEV is a platform that can be extended to the wide area of policy schemes for support of EVs and EVs integration to the power grid and Electricity Market. The future work related to this thesis is summarized in Table 29.

**Table 29: Future work related to this thesis**

| Area | Future work |
|---|---|
| Electricity market | Bilateral forward contracts in the electricity market, participation of EVs in power regulation and automatic reserve, PPA for to EMMEV |
| Policy scheme related to low-carbon vehicle | Rebate system, tax reeducation and incentive for purchasing EV to EMMEV, Calculation of emissions from electricity generation and investigate the effect of replacement of electricity as fuel (considering the whole life cycle) |
| Micro grid | VPP and blockchain and Fast Charging, Larger size of EVs battery |

The primary idea behind developing EMMEV was to create a platform in which the effects of different support schemes for low-carbon vehicles on the electricity market can be investigated. The interdependence of transportation policies and the electricity market is increasing due to increasing number of Electric Vehicles, while these two historically had low interdependence. This thesis both introduced EMMEV and started the investigation of the impact of LCFS on the electricity market. In the future, EMMEV will be used to investigate the impact of other low-carbon policies on the electricity market.

From support scheme for low-carbon vehicles perspective, a rebate systems, tax reductions and incentives for purchasing EVs [23] can be added to EMMEV and the effects of those policies on the electricity market to be investigated.

From Electricity Market perspective, bilateral contracts can be added to the model and the effects of EVs on the Power Regulation and Automatic Reserve can be investigated. These days, Power Purchase Agreements (PPA) between the generation units and end consumers is getting more and more popular. One of the future work in this thesis can be related to added PPA to the model and add the flexibility of a PPA into EMMEV.

EVs are mainly meant to reduce carbon emissions in transportation sector. There is a question on how much the EVs can reduce carbon emissions. The main factor is the amount of electricity generation from renewable resources. One future study could be to investigate emissions reduction in transportation by adding EVs to the fleet and testing this with different scenarios.

In this thesis, EMMEV and OPSC are two separate pieces of study. One future work could be to integrate those two models and have a complete value chain of electricity from generation to electricity market, incentives for EVs and finally to EVs charging. In this way, the effects of different support schemes on the operation of the grid can be also investigated.

From OPSC, the model can be prototyped and used in the real charges for the operations of the micro grids. In addition, OPSC can be tested with other optimization platforms to compare the results. On the other hand, control and design of a fast charging or semi-fast charging solution within a microgrid is the future development in the charging of the EVs.

On the electricity retail side of an ESCo, the renewable electricity generation can be sold to EVs through Virtual Power Plants (VPP). Definition of a VPP within EMMEV can be an interesting future work from this thesis.

Nowadays one of the most popular application of blockchain technology is in renewable electricity generation. A blockchain set-up within EMMEV where the renewable electricity generation units and EV drivers can trade electricity directly can be an interesting future study after this thesis.

Flexibility taken from the grid and Vehicle to Grid (V2G) is another interesting add-in to EMMEV. This can complete the functionality of the model and give more insights to about reliability of different policy schemes.

The LCFS is an efficient policy driver to decrease carbon emissions in transportation in the long term and in wide geographical areas. This can be a good fit on the European Commission level, so each member state, apart from their local policies to decrease emissions in transportation, can contribute to a future green vision for transportation in Europe.

### 7.3 Future of ENERGY X.0, MET and EMMEV

With no doubt, climate change is the main existential threat to all of us living in this plant. In addition, there is no uncertainty that energy sector is prime responsible [124]. We are all responsible to pay our share to save our planet. I would pay my share with a concept (to be research group) called ENERGY X.0: Future of Energy Systems.

**Figure 49 ENERGY X.0 Logo**

There is website for the ENERGY X.0 [29]. Part of ENERGY X.0, MET is developed in this thesis and it is tested with LCFS as a policy for reducing emissions in transportation and micro grid management of the grid with EVs. In the future ENERGY X.0, MET and EMMEV will stay in the research world with more publications and contributions to save our planet and children from climate change. The latest publication on ENERGY X.0 is called Organic Data Centers to tackled climate change with recovering the excess heat from data centers [20]. More will be developed and published after this thesis to contribute forming the future of energy system.

# References


1. Kirsch, D.A., *The electric vehicle and the burden of history*. 2000.
2. *International Energy Agency Statistics*. Available from: http://www.iea.org/stats/index.asp.
3. Jaramillo, P., et al., *Greenhouse gas implications of using coal for transportation: Life cycle assessment of coal-to-liquids, plug-in hybrids, and hydrogen pathways.* Energy Policy, 2009. **37**(7): p. 2689-2695.
4. *Global EV Outlook 2018 Towards cross-modal electrification*. 2018, International Energy Agency.
5. *EV30@30 Campaign*. 2018, International Energy Agency.
6. *Enhancing Grid Resilience with Integrated Storage from Electric Vehicles*. 2018, Recommendations for the U.S. Department of Energy.
7. Aman Verma, P.S., *How Green is an EV on a Well to Wheel Basis*. 2018, Wood Mackenzie
8. Karnama, A., *Analysis of Integration of Plug-in Hybrid Electric Vehicles in the Distribution Grid*. 2009: Stockholm.
9. Lopes, J.A.P., F.J. Soares, and P.M.R. Almeida, *Integration of Electric Vehicles in the Electric Power System.* Proceedings of the IEEE, 2010. **PP**(99): p. 1-16.
10. Galus, M.D., M. Zima, and G. Andersson, *On integration of plug-in hybrid electric vehicles into existing power system structures.* Energy Policy, 2010. **38**(11): p. 6736-6745.
11. Eppstein, M.J., et al., *An agent-based model to study market penetration of plug-in hybrid electric vehicles.* Energy Policy, 2011. **39**(6): p. 3789-3802.
12. Sprei, F. and D. Bauner, *Incentives impact on EV markets*. 2011, Viktoria Institute.
13. *PoMo Predicts prices in a hydro-thermal power system*, Sweco, Editor. 2012.
14. Ventosa, M., et al., *Electricity market modeling trends.* Energy Policy, 2005. **33**(7): p. 897-913.
15. Silva Fernandes, J.F., *Modeling Adverse Weather and Electric Vehicles Integration in the Distribution Systems Reliability and Assessment*. 2012, Faculty of Engineering University of Porto.
16. Houghton, E., *Climate change 1995: The science of climate change: contribution of working group I to the second assessment report of the Intergovernmental Panel on Climate Change*. Vol. 2. 1996: Cambridge University Press.
17. Chu, S. and A. Majumdar, *Opportunities and challenges for a sustainable energy future.* nature, 2012. **488**(7411): p. 294-303.
18. Karnama, A., *ENERGY X. 0: Future of energy systems.* Results in Engineering, 2019. **3**: p. 100029.
19. Boyle, G., *Renewable energy*. 2004: Open University.
20. Karnama, A., E.B. Haghighi, and R. Vinuesa, *Organic data centers: A sustainable solution for computing facilities.* Results in Engineering, 2019. **4**: p. 100063.
21. Eberle, U. and R. von Helmolt, *Sustainable transportation based on electric vehicle concepts: a brief overview.* Energy & Environmental Science, 2010. **3**(6): p. 689-699.
22. Fazeli, R. and V. Leal, *A multi-criteria evaluation framework for alternative light-duty vehicles technologies.* International Journal of Multicriteria Decision Making (IJMCDM), 2011. **Volume 1**: p. 230 - 251.
23. European Automobile Manufacturers Association, *Overview of CO2-based motor vehicle taxes in the EU.* 2013. **4**.
24. Sierzchula, W., et al., *The influence of financial incentives and other socio-economic factors on electric vehicle adoption.* Energy Policy, 2014. **68**: p. 183-194.
25. Lopes, J.A.P., et al. *Quantification of technical impacts and environmental benefits of electric vehicles integration on electricity grids*. in *Advanced Electromechanical Motion Systems & Electric Drives Joint Symposium, 2009. ELECTROMOTION 2009. 8th International Symposium on*. 2009.
26. Yeh, S., et al., *National Low Carbon Fuel Standard: Policy Design Recommendations.* Available at SSRN 2105897, 2012.
27. Farrell, A.E. and D. Sperling, *A low-carbon fuel standard for California, Part 1: Technical analysis.* Institute of Transportation Studies, 2007.
28. Rivier, M. and e. al, *MERGE (Mobile Energy Rescources in Grids of Electricity) Project - Scenarios and roadmap for deployment of EV in three European regions: Recommendations for policy makers and regulators*. 2011, European Commision.
29. *ENERGY X.0*. 2020; Available from: https://www.energyx0.com/.
30. Greene, D.L., et al., *Feebates, rebates and gas-guzzler taxes: a study of incentives for increased fuel economy.* Energy policy, 2005. **33**(6): p. 757-775.

31. Lade, G.E. and C.Y.C. Lin Lawell, *The design and economics of low carbon fuel standards.* Research in Transportation Economics, 2015. **52**: p. 91-99.
32. Yeh, S. and J. Witcover, *Status Review of California's Low Carbon Fuel Standard, January 2014. Institute of Transportation Studies, University of California*. 2013, Davis Research Report UCD-ITS-RR-14-01.
33. Yeh, S. and J. Witcover, *Status Review of California's Low Carbon Fuel Standard-- January 2014 Issue: University of California*. 2014, Davis.
34. Berry, T. and M. Jaccard, *The renewable portfolio standard:: design considerations and an implementation survey.* Energy Policy, 2001. **29**(4): p. 263-277.
35. Fagiani, R., J. Barquín, and R. Hakvoort, *Risk-based assessment of the cost-efficiency and the effectivity of renewable energy support schemes: Certificate markets versus feed-in tariffs.* Energy Policy, 2013. **55**(0): p. 648-661.
36. Tudor, G.G., *The Norway-Sweden certificate market in renewable electricity: A model for the European Union*. 2012, University of Texas School of Law.
37. Nilsson, J., *The electricity certificate system 2012* 2012, Swedish Energy Agency.
38. Air Resources Board - California. *Low Carbon Fuel Standard*. 2016 [cited 2016 05 August]; Available from: http://www.arb.ca.gov/fuels/lcfs/lcfs.htm.
39. oregon.gov, S.o.O.D.o.E.Q., *Supporting Documentation for Calculating Credits and Deficits - Agenda Item B*. 2010.
40. Air Resources Board - California, *Low Carbon Fuel Standard - Final Regulation Order*. 2012, Air Resources Board - California.
41. Air Resources Board - California, *Low Carbon Fuel Standard Regulatory Guidance 16-04 - LCFS Electricity Program FAQs*. 2016.
42. Green, R., *The electricity contract market in England and Wales.* The Journal of Industrial Economics, 1999. **47**(1): p. 107-124.
43. Bessa, R.J., et al., *Optimized Bidding of a EV Aggregation Agent in the Electricity Market.* Smart Grid, IEEE Transactions on, 2012. **3**(1): p. 443-452.
44. Bessa, R.J. and M.A. Matos, *Global against divided optimization for the participation of an EV aggregator in the day-ahead electricity market. Part I: Theory.* Electric Power Systems Research, 2013. **95**(0): p. 309-318.
45. Bessa, R.J. and M.A. Matos, *Economic and technical management of an aggregation agent for electric vehicles: a literature survey.* European Transactions on Electrical Power, 2011: p. n/a-n/a.
46. Bessa, R.J. and M.A. Matos. *The role of an aggregator agent for EV in the electricity market*. in *Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2010), 7th Mediterranean Conference and Exhibition on*. 2010.
47. Gomes de Sousa Bento Bessa; Ricardo Jorge, *Methodologies for the participation of an Electric Vehicle' aggregation in the electricity market*, in *PhD thesis*. 2013, Faculty of Engineering University of Porto.
48. Xia, M., et al., *Aggregator-Based Interactive Charging Management System for Electric Vehicle Charging.* Energies, 2016. **9**(3): p. 159.
49. Bang, C., et al., *EVs and the Current Nordic Electricity Market*, in *Grid Integration of Electric Vehicles in Open Electricity Markets*. 2013, John Wiley & Sons Ltd. p. 32-53.
50. Søndergren, C., et al., *Electric Vehicles in Future Market Models*, in *Grid Integration of Electric Vehicles in Open Electricity Markets*. 2013, John Wiley & Sons Ltd. p. 54-81.
51. Stefanidou, I. and M. Zerva, *Control Strategies for Under-frequency Load Shedding*. 2009, EEH – Power Systems Laboratory: Swiss Federal Institute of Technology (ETH) Zurich.
52. Karnama, A. and V. Knazkins. *Scenario-based investigation of the effects of Plug-in Hybrid Electric Vehicles (PHEVs) in 11 kV substations in Stockholm*. in *Energy Market (EEM), 2010 7th International Conference on the European*. 2010.
53. Bertling, L., et al. *Integration of plug in hybrid electric vehicles and electric vehicles - experience from Sweden*. in *Power and Energy Society General Meeting, 2010 IEEE*. 2010.
54. Ilic, x, and M. D., *Dynamic Monitoring and Decision Systems for Enabling Sustainable Energy Services.* Proceedings of the IEEE, 2011. **99**(1): p. 58-79.
55. Bandivadekar, A., *Evaluating the impact of Advanced Vehicle and Fuel Technologies in US Light-Duty Vehicle Fleet*, in *Technology and Policy*. 2008, Massachusetts Institute of Technology.
56. Offer, G.J., et al., *Comparative analysis of battery electric, hydrogen fuel cell and hybrid vehicles in a future sustainable road transport system.* Energy Policy, 2010. **38**(1): p. 24-29.
57. Lopes, J.A.P., F.J. Soares, and P.M.R. Almeida. *Identifying management procedures to deal with connection of Electric Vehicles in the grid*. in *PowerTech, 2009 IEEE Bucharest*. 2009.

58. Karnama, A., F.O. Resende, and J.A.P. Lopes. *Optimal Management of Battery Charging of Electric Vehicles: A New Microgrid Feature*. in *PowerTech*. 2011. Trondheim, Norway.
59. Sterling, L. and T. Kuldar;. *The Art of Agent-Oriented Modeling*. The MIT Press, Cambridge, Massachusetts.
60. Parsons, S. and M. Wooldridge, *Game Theory and Decision Theory in Multi-Agent Systems*, in *Autonomous Agents and Multi-Agent Systems*. 2002. p. 243-254.
61. McArthur, S.D.J., et al., *Multi-Agent Systems for Power Engineering Applications;Part I: Concepts, Approaches, and Technical Challenges.* Power Systems, IEEE Transactions on, 2007. **22**(4): p. 1743-1752.
62. Wooldridge, M., *Multi Agent Systems*. Second ed. 2009, Glascow: John Wiley & Sons.
63. Niazi, M. and A. Hussain, *Agent-based computing from multi-agent systems to agent-based Models: a visual survey* Institute of Computing Science and Mathematics, School of Natural Sciences, University Of Stirling, Scotland, UK.
64. *NetLogo*. 2013 [cited 2013 March]; Available from: http://ccl.northwestern.edu/netlogo/.
65. *RePast*. 2013 [cited 2013 March]; Available from: http://repast.sourceforge.net/.
66. Specification, F.I.C.A., *Foundation for Intelligent Physical Agents, 2000*. 2004.
67. Ventosa, M., et al., *Electricity market modeling trends.* Energy Policy, 2005. **33**(7): p. 897-913.
68. E. Farrell, A. and D. Sperling, *A Low-Carbon Fuel Standard for California, Part 1: Technical Analysis*. 2007, UC Berkeley, UC Davis.
69. Booch, G., J. Rumbaugh, and I. Jacobson, *Unified Modeling Language User Guide*. 1998: Addison Wesley.
70. *UML Basic Notations*. [cited 2013 1 October]; Available from: http://www.tutorialspoint.com/uml/uml_basic_notations.htm.
71. Venkat. *UML*. 2011 [cited 2013 1 October]; Available from: http://www.noesisbase.com/noesisbase/views/articles/8f5da9c923834008853388e6ddbdd97a.aspx?articlepid=15.
72. Uslar, M. and J. Trefke, *Applying the Smart Grid Architecture Model SGAM to the EV Domain*, in *Proceedings of the 28th EnviroInfo 2014 Conference, Oldenburg, Germany*. September 10-12, 2014.
73. Kempton, W. and J. Tomić, *Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy.* Journal of Power Sources, 2005. **144**(1): p. 280-294.
74. Gómez-Expósito, A., A.J. Conejo, and C. Cañizares, *Electric energy systems: analysis and operation*. 2008: CRC Press.
75. Han, S., S. Han, and K. Sezaki, *Estimation of Achievable Power Capacity From Plug-in Electric Vehicles for V2G Frequency Regulation: Case Studies for Market Participation.* IEEE Transactions on Smart Grid, 2011. **2**(4): p. 632-641.
76. Breeze, P., *Power Generation Technologies*. 2005: Elsevier Science.
77. Singh, H., S. Hao, and A. Papalexopoulos, *Transmission congestion management in competitive electricity markets.* IEEE Transactions on Power Systems, 1998. **13**(2): p. 672-680.
78. Andreasson, J., Centeno Lopez, Eva, Jakobsson, Tobias, Joensson, Anders, & Larsson, Marcus. , *The Swedish Energy Agency's methodology for long-term energy projections.* 2006.
79. Kirschen, D.S., et al., *Factoring the elasticity of demand in electricity prices.* IEEE Transactions on Power Systems, 2000. **15**(2): p. 612-617.
80. European Commision, *Regulatory Recommendations for the Deployment of Flexibility*. 2015, European Commission - EG3 REPORT SMART GRID TASK FORCE.
81. BRUCE, J., B. KLASMAN, and L. SCHUMACHER, *The future electricity intraday market design.* 2019.
82. Holmberg, P. and E. Lazarczyk, *Comparison of congestion management techniques: Nodal, zonal and discriminatory pricing.* The Energy Journal, 2015. **36**(2).
83. Tengshun, P. and K. Tomsovic, *Congestion influence on bidding strategies in an electricity market.* IEEE Transactions on Power Systems, 2003. **18**(3): p. 1054-1061.
84. Lo, K.L., Y.S. Yuen, and L.A. Snider. *Congestion management in deregulated electricity markets*. in *DRPT2000. International Conference on Electric Utility Deregulation and Restructuring and Power Technologies. Proceedings (Cat. No.00EX382)*. 2000.
85. Yusoff, N.I., A.A.M. Zin, and A.B. Khairuddin. *Congestion management in power system: A review*. in *2017 3rd International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET)*. 2017.
86. Philipsen, R., M. de Weerdt, and L. de Vries. *Auctions for congestion management in distribution grids*. in *2016 13th International Conference on the European Energy Market (EEM)*. 2016. IEEE.
87. Marmiroli, M., et al., *Market Splitting Algorithm for Congestion Management in Electricity Spot Market.* 2006.
88. Dijk, J. and B. Willems, *The effect of counter-trading on competition in electricity markets.* Energy Policy, 2011. **39**(3): p. 1764-1773.

89. Bjørndal, E., M. Bjørndal, and L. Rud. *Congestion management by dispatch or re-dispatch: flexibility costs and market power effects*. in *2013 10th International Conference on the European Energy Market (EEM)*. 2013. IEEE.
90. Farahani, V.Z., A. Kazemi, and A.B. Majd. *Congestion management in bilateral based power market by FACTS devices and load curtailments*. in *2006 IEEE Power India Conference*. 2006.
91. Hogan, W.W., *Transmission congestion: the nodal-zonal debate revisited.* Harvard University, John F. Kennedy School of Government, Center for Business and Government. Retrieved August, 1999. **29**(4).
92. Sarfati, M., M.R. Hesamzadeh, and P. Holmberg, *Production efficiency of nodal and zonal pricing in imperfectly competitive electricity markets.* Energy Strategy Reviews, 2019. **24**: p. 193-206.
93. Silva, J.O.F. and P. Cuervo. *Allocating Congestion Management Costs through Use-Based Principle of Equivalent Bilateral Exchanges*. in *2008 5th International Conference on the European Electricity Market*. 2008.
94. Weibelzahl, M., *Nodal, zonal, or uniform electricity pricing: how to deal with network congestion.* Frontiers in Energy, 2017. **11**(2): p. 210-232.
95. Hakvoort, R. and L.J. Vries, *An economic assessment of congestion management methods for electricity transmission networks.* Competition and Regulation in Network Industries, 2002. **3**: p. 425-467.
96. Agency, I.-I.R., *INCREASING SPACE GRANULARITY IN ELECTRICITY MARKETS INNOVATION LANDSCAPE BRIEF*. 2019.
97. NationMaster. *Motor vehicles per 1000 people: Countries Compared*. 2014 [cited 2016; Available from: http://www.nationmaster.com/country-info/stats/Transport/Road/Motor-vehicles-per-1000-people.
98. Statistics Sweden. 2016; Available from: http://www.scb.se/en_/.
99. Statistics Portugal, 2016.
100. E.ON. *E.ON Sverige*. 2016; Available from: https://www.eon.se/.
101. Jardini, J.A., et al., *Daily load profiles for residential, commercial and industrial low voltage consumers.* IEEE Transactions on power delivery, 2000. **15**(1): p. 375-380.
102. Holmes, A., et al., *Introductory Business Statistics*. 2018: OpenStax College, Rice University.
103. Lee, E.-K., et al., *Design and Implementation of a Microgrid Energy Management System.* Sustainability, 2016. **8**: p. 1143.
104. Lijesen, M.G., *The real-time price elasticity of electricity.* Energy economics, 2007. **29**(2): p. 249-258.
105. Branch, E.R., *Short run income elasticity of demand for residential electricity using consumer expenditure survey data.* The Energy Journal, 1993: p. 111-121.
106. Espey, J.A. and M. Espey, *Turning on the lights: A meta-analysis of residential electricity demand elasticities.* Journal of Agricultural and Applied Economics, 2004. **36**(1): p. 65-81.
107. Krishnamurthy, C.K. and B. Kriström, *Energy demand and income elasticity: a cross-country analysis.* Available at SSRN 2310005, 2013.
108. *Environmental Assessment of Plug-In Hybrid Electric Vehicles Volume 1: Nationwide Greenhouse Gas Emissions*. EPRI, Palo Alto, CA: 2007. 1015325.
109. Bendeing, S., et al., *Mobile Energy Resources in Grids of Electricity (MERGE), Specifications for EV-grid interfacing, communication and smart metering technologies, including traffic patterns and human behavior description*. 2010, European Union.
110. Rivier, M. and e. al., *MERGE (Mobile Energy Rescources in Grids of Electricity) Project - New actors and business models for the integration of EV in power system*. 2011, European Commision.
111. Joskow, P.L., *Restructuring, competition and regulatory reform in the US electricity sector.* Journal of Economic perspectives, 1997. **11**(3): p. 119-138.
112. Sensfuß, F., M. Ragwitz, and M. Genoese, *The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany.* Energy policy, 2008. **36**(8): p. 3086-3094.
113. Schneider, J., et al., *Asset management techniques.* International Journal of Electrical Power & Energy Systems, 2006. **28**(9): p. 643-654.
114. *No Tax for Solar Generation*. Available from: http://www.skatteverket.se/privat/fastigheterbostad/mikroproduktionavfornybarel/forsaljningavoverskottsel.4.3aa8c78a1466c58458750f7.html.
115. Axsen, J. and K.S. Kurani, *Hybrid, plug-in hybrid, or electric—What do car buyers want?* Energy Policy, 2013. **61**: p. 532-543.
116. Lopes, J.A.P., C.L. Moreira, and A.G. Madureira, *Defining control strategies for MicroGrids islanded operation.* Power Systems, IEEE Transactions on, 2006. **21**(2): p. 916-924.
117. Peças Lopes, J.A., et al., *Identification of control and management strategies for LV unbalanced microgrids with plugged-in electric vehicles.* Electric Power Systems Research, 2010. **80**(8): p. 898-906.
118. *Portugal Renewable Energy Policy Review*. 2009, EREC (European Renwable Energy Coucil).

119. Weise, T., *Global Optimization Algorithms – Theory and Application*. 2009.
120. Carol S. Cheng, D.S., *A THREE-PHASE POWER FLOW METHOD FOR REAL-TIME DISTRIBUTION SYSTEM ANALYSIS.* IEEE Transactions on Power Systems, , May 1995. **Vol. 10**(No. 2).
121. Miranda, V. and N. Fonseca. *EPSO-evolutionary particle swarm optimization, a new algorithm with applications in power systems*. in *IEEE/PES Transmission and Distribution Conference and Exhibition*. 2002.
122. Robert Ball, N.K., Marcus Alexander, Ed Bower, *Modelling electric storage devices for EV WP2 Task 2.1 Deliverable D2.1*. 2010.
123. Weidlich, A., et al., *Studying the effects of CO2 emissions trading on the electricity market: A multi-agent-based approach*, in *Emissions Trading*, R. Antes, B. Hansjürgens, and P. Letmathe, Editors. 2008, Springer New York. p. 91-101.
124. Agency, I.E., *World Energy Outlook 2019.* 2019.

# Appendix 1
# Generation units

The price for each interval of electricity generation (total 4 intervals) are shown in the following table. The IndentityID is the agent number. The generation type connected to each Wind (1), Hydro (2), Nuclear (3), thermal (4) and solar is (5) as shown in the table below. The wind and solar generation units always bid at one level cost. The generation units by each type of generation is shown in the table below.

| | Country 1, Area 1 | Country 1, Area 2 | Country 2, Area 1 | Country 2, Area 2 |
|---|---|---|---|---|
| Wind (MW) | 2400 | 2500 | 3200 | 4300 |
| Hydro (MW) | 2300 | 3900 | 2800 | 3100 |
| Nuclear (MW) | 3500 | 3200 | 3500 | 3400 |
| Thermal (MW) | 2100 | 2800 | 3900 | 3100 |
| Solar (MW) | 100 | 200 | 300 | 900 |
| Total (MW) | 10400 | 12600 | 13700 | 14800 |

| Generation Capacity (MW) | Interval 1 From (MW) | Interval 1 To (MW) | Price Interval 1 (€/MWh) | Interval 2 From (MW) | Interval 2 To (MW) | Price Interval 2 (€/MWh) | Interval 3 From (MW) | Interval 3 To (MW) | Price Interval 3 (€/MWh) | Interval4 From (MW) | Interval 4 To (MW) | Price Interval 4 (€/MWh) | Country | RegionID | Entity ID | Generation type |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 100 | 0 | [redacted] | | | | | | | | | 100 | 20 | 1 | 1 | 1 | 5 |
| 1200 | 0 | [redacted] | | | | | | | | | 1200 | 20 | 1 | 1 | 3 | 1 |
| 1100 | 0 | 550 | 21 | 551 | 770 | 24 | 771 | 990 | 27 | 991 | 1100 | 30 | 1 | 1 | 5 | 2 |
| 800 | 0 | 400 | 21 | 401 | 560 | 24 | 561 | 720 | 27 | 721 | 800 | 30 | 1 | 1 | 3 | 2 |
| 700 | 0 | [redacted] | | | | | | | | | 700 | 20 | 1 | 1 | 1 | 1 |
| 300 | 0 | 150 | 28 | 151 | 210 | 32 | 211 | 270 | 36 | 271 | 300 | 40 | 1 | 1 | 3 | 3 |
| 500 | 0 | 250 | 28 | 251 | 350 | 32 | 351 | 450 | 36 | 451 | 500 | 40 | 1 | 1 | 4 | 3 |
| 500 | 0 | [redacted] | | | | | | | | | 500 | 20 | 1 | 1 | 3 | 1 |
| 400 | 0 | 200 | 21 | 201 | 280 | 24 | 281 | 360 | 27 | 361 | 400 | 30 | 1 | 1 | 5 | 2 |
| 400 | 0 | 200 | 28 | 201 | 280 | 32 | 281 | 360 | 36 | 361 | 400 | 40 | 1 | 1 | 5 | 3 |
| 300 | 0 | 150 | 49 | 151 | 210 | 56 | 211 | 270 | 63 | 271 | 300 | 70 | 1 | 1 | 3 | 4 |
| 200 | 0 | 100 | 28 | 101 | 140 | 32 | 141 | 180 | 36 | 181 | 200 | 40 | 1 | 1 | 1 | 3 |
| 200 | 0 | 100 | 49 | 101 | 140 | 56 | 141 | 180 | 63 | 181 | 200 | 70 | 1 | 1 | 5 | 4 |
| 700 | 0 | 350 | 28 | 351 | 490 | 32 | 491 | 630 | 36 | 631 | 700 | 40 | 1 | 1 | 5 | 3 |
| 800 | 0 | 400 | 28 | 401 | 560 | 32 | 561 | 720 | 36 | 721 | 800 | 40 | 1 | 1 | 3 | 3 |
| 700 | 0 | 350 | 49 | 351 | 490 | 56 | 491 | 630 | 63 | 631 | 700 | 70 | 1 | 1 | 3 | 4 |
| 900 | 0 | 450 | 49 | 451 | 630 | 56 | 631 | 810 | 63 | 811 | 900 | 70 | 1 | 1 | 5 | 4 |
| 200 | 0 | 100 | 28 | 101 | 140 | 32 | 141 | 180 | 36 | 181 | 200 | 40 | 1 | 1 | 3 | 3 |
| 200 | 0 | 100 | 28 | 101 | 140 | 32 | 141 | 180 | 36 | 181 | 200 | 40 | 1 | 1 | 1 | 3 |
| 200 | 0 | 100 | 28 | 101 | 140 | 32 | 141 | 180 | 36 | 181 | 200 | 40 | 1 | 1 | 5 | 3 |
| 1000 | 0 | 500 | 28 | 501 | 700 | 32 | 701 | 900 | 36 | 901 | 1000 | 40 | 1 | 2 | 3 | 3 |
| 1000 | 0 | [redacted] | | | | | | | | | 1000 | 20 | 1 | 2 | 3 | 1 |
| 2000 | 0 | 1000 | 21 | 1001 | 1400 | 24 | 1401 | 1800 | 27 | 1801 | 2000 | 30 | 1 | 2 | 5 | 2 |
| 500 | 0 | 250 | 49 | 251 | 350 | 56 | 351 | 450 | 63 | 451 | 500 | 70 | 1 | 2 | 3 | 4 |
| 1000 | 0 | 500 | 21 | 501 | 700 | 24 | 701 | 900 | 27 | 901 | 1000 | 30 | 1 | 2 | 3 | 2 |
| 800 | 0 | 400 | 49 | 401 | 560 | 56 | 561 | 720 | 63 | 721 | 800 | 70 | 1 | 2 | 3 | 4 |
| 900 | 0 | 450 | 28 | 451 | 630 | 32 | 631 | 810 | 36 | 811 | 900 | 40 | 1 | 2 | 1 | 3 |
| 900 | 0 | 450 | 28 | 451 | 630 | 32 | 631 | 810 | 36 | 811 | 900 | 40 | 1 | 2 | 5 | 3 |
| 900 | 0 | [redacted] | | | | | | | | | 900 | 20 | 1 | 2 | 5 | 1 |
| 500 | 0 | 250 | 49 | 251 | 350 | 56 | 351 | 450 | 63 | 451 | 500 | 70 | 1 | 2 | 5 | 4 |
| 400 | 0 | 200 | 21 | 201 | 280 | 24 | 281 | 360 | 27 | 361 | 400 | 30 | 1 | 2 | 3 | 2 |
| 300 | 0 | [redacted] | | | | | | | | | 300 | 20 | 1 | 2 | 1 | 1 |
| 200 | 0 | 100 | 49 | 101 | 140 | 56 | 141 | 180 | 63 | 181 | 200 | 70 | 1 | 2 | 1 | 4 |
| 300 | 0 | [redacted] | | | | | | | | | 300 | 20 | 1 | 2 | 3 | 1 |
| 400 | 0 | 200 | 28 | 201 | 280 | 32 | 281 | 360 | 36 | 361 | 400 | 40 | 1 | 2 | 3 | 3 |
| 500 | 0 | 250 | 21 | 251 | 350 | 24 | 351 | 450 | 27 | 451 | 500 | 30 | 1 | 2 | 3 | 2 |
| 600 | 0 | 300 | 49 | 301 | 420 | 56 | 421 | 540 | 63 | 541 | 600 | 70 | 1 | 2 | 5 | 4 |
| 200 | 0 | [redacted] | | | | | | | | | 200 | 20 | 1 | 2 | 1 | 5 |
| 100 | 0 | 50 | 49 | 51 | 70 | 56 | 71 | 90 | 63 | 91 | 100 | 70 | 1 | 2 | 3 | 4 |
| 100 | 0 | 50 | 49 | 51 | 70 | 56 | 71 | 90 | 63 | 91 | 100 | 70 | 1 | 2 | 5 | 4 |
| 1000 | 0 | [redacted] | | | | | | | | | 1000 | 20 | 2 | 1 | 1 | 1 |
| 1000 | 0 | [redacted] | | | | | | | | | 1000 | 20 | 2 | 1 | 3 | 1 |
| 1500 | 0 | 750 | 21 | 751 | 1050 | 24 | 1051 | 1350 | 27 | 1351 | 1500 | 30 | 2 | 1 | 5 | 2 |
| 2000 | 0 | 1000 | 49 | 1001 | 1400 | 56 | 1401 | 1800 | 63 | 1801 | 2000 | 70 | 2 | 1 | 3 | 4 |
| 900 | 0 | 450 | 21 | 451 | 630 | 24 | 631 | 810 | 27 | 811 | 900 | 30 | 2 | 1 | 3 | 2 |
| 700 | 0 | 350 | 49 | 351 | 490 | 56 | 491 | 630 | 63 | 631 | 700 | 70 | 2 | 1 | 3 | 4 |
| 800 | 0 | 400 | 28 | 401 | 560 | 32 | 561 | 720 | 36 | 721 | 800 | 40 | 2 | 1 | 3 | 3 |
| 600 | 0 | 300 | 28 | 301 | 420 | 32 | 421 | 540 | 36 | 541 | 600 | 40 | 2 | 1 | 5 | 3 |
| 800 | 0 | [redacted] | | | | | | | | | 800 | 20 | 2 | 1 | 5 | 1 |
| 700 | 0 | 350 | 28 | 351 | 490 | 32 | 491 | 630 | 36 | 631 | 700 | 40 | 2 | 1 | 3 | 3 |
| 400 | 0 | 200 | 28 | 201 | 280 | 32 | 281 | 360 | 36 | 361 | 400 | 40 | 2 | 1 | 3 | 3 |
| 300 | 0 | [redacted] | | | | | | | | | 300 | 20 | 2 | 1 | 1 | 1 |
| 200 | 0 | 100 | 49 | 101 | 140 | 56 | 141 | 180 | 63 | 181 | 200 | 70 | 2 | 1 | 1 | 4 |
| 100 | 0 | [redacted] | | | | | | | | | 100 | 20 | 2 | 1 | 5 | 1 |
| 500 | 0 | 250 | 49 | 251 | 350 | 56 | 351 | 450 | 63 | 451 | 500 | 70 | 2 | 1 | 3 | 4 |
| 400 | 0 | 200 | 21 | 201 | 280 | 24 | 281 | 360 | 27 | 361 | 400 | 30 | 2 | 1 | 3 | 2 |
| 700 | 0 | 350 | 28 | 351 | 490 | 32 | 491 | 630 | 36 | 631 | 700 | 40 | 2 | 1 | 5 | 3 |
| 300 | 0 | 150 | 28 | 151 | 210 | 32 | 211 | 270 | 36 | 271 | 300 | 40 | 2 | 1 | 1 | 3 |
| 500 | 0 | 250 | 49 | 251 | 350 | 56 | 351 | 450 | 63 | 451 | 500 | 70 | 2 | 1 | 5 | 4 |
| 300 | 0 | [redacted] | | | | | | | | | 300 | 20 | 2 | 1 | 5 | 5 |
| 1000 | 0 | [redacted] | | | | | | | | | 1000 | 20 | 2 | 2 | 1 | 1 |
| 1000 | 0 | | | | | | | | | | 1000 | 20 | 2 | 2 | 3 | 1 |
| 1000 | 0 | | | | | | | | | | 1000 | 20 | 2 | 2 | 5 | 1 |
| 1000 | 0 | 500 | 21 | 501 | 700 | 24 | 701 | 900 | 27 | 901 | 1000 | 30 | 2 | 2 | 3 | 2 |
| 1300 | 0 | [redacted] | | | | | | | | | 1300 | 20 | 2 | 2 | 3 | 1 |
| 1700 | 0 | 850 | 49 | 851 | 1190 | 56 | 1191 | 1530 | 63 | 1531 | 1700 | 70 | 2 | 2 | 3 | 4 |
| 1000 | 0 | 500 | 28 | 501 | 700 | 32 | 701 | 900 | 36 | 901 | 1000 | 40 | 2 | 2 | 5 | 3 |
| 900 | 0 | 450 | 28 | 451 | 630 | 32 | 631 | 810 | 36 | 811 | 900 | 40 | 2 | 2 | 3 | 3 |
| 800 | 0 | 400 | 21 | 401 | 560 | 24 | 561 | 720 | 27 | 721 | 800 | 30 | 2 | 2 | 5 | 2 |
| 700 | 0 | 350 | 28 | 351 | 490 | 32 | 491 | 630 | 36 | 631 | 700 | 40 | 2 | 2 | 3 | 3 |
| 800 | 0 | 400 | 28 | 401 | 560 | 32 | 561 | 720 | 36 | 721 | 800 | 40 | 2 | 2 | 3 | 3 |
| 800 | 0 | 400 | 21 | 401 | 560 | 24 | 561 | 720 | 27 | 721 | 800 | 30 | 2 | 2 | 1 | 2 |
| 300 | 0 | 150 | 21 | 151 | 210 | 24 | 211 | 270 | 27 | 271 | 300 | 30 | 2 | 2 | 1 | 2 |
| 200 | 0 | 100 | 21 | 101 | 140 | 24 | 141 | 180 | 27 | 181 | 200 | 30 | 2 | 2 | 5 | 2 |
| 700 | 0 | 350 | 49 | 351 | 490 | 56 | 491 | 630 | 63 | 631 | 700 | 70 | 2 | 2 | 3 | 4 |
| 700 | 0 | 350 | 49 | 351 | 490 | 56 | 491 | 630 | 63 | 631 | 700 | 70 | 2 | 2 | 3 | 4 |
| 300 | 0 | [redacted] | | | | | | | | | 300 | 20 | 2 | 2 | 5 | 5 |
| 200 | 0 | | | | | | | | | | 200 | 20 | 2 | 2 | 1 | 5 |
| 100 | 0 | | | | | | | | | | 100 | 20 | 2 | 2 | 5 | 5 |
| 300 | 0 | | | | | | | | | | 300 | 20 | 2 | 2 | 5 | 5 |

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|---|---|---|---|---|
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# Appendix 2
## Agents Onthology and classes in EMMEV

## A2.1 GenerationUnit

| GenerationUnit |
|---|
| -installationYear<br>-generationCapacity<br>-technologyName : string<br>-technologyCode : double<br>-fullLoadTime : double<br>-LRMC : double<br>-WACC : double<br>-variableCost : double<br>-country : int<br>-regionID : int<br>-certificate : double<br>-fixedOpex : double<br>-willingnessToSell : double<br>-check : int<br>-entity : int |
| +getForecastedNumberOfCertificates() : double<br>+getInstallationYear() : double<br>+getGenerationCapacity() : double<br>+getTechnologyName() : string<br>+getTechnologyCode() : int<br>+getFullLoadTime() : double<br>+getLRMCPerfectCompetition() : double<br>+getLRMC() : double<br>+getWACC() : double<br>+getVariableCost() : double<br>+getCountry() : int<br>+getRegionID() : int<br>+getCertificate() : double<br>+getFixedOPEX() : double<br>+getWillingnessToSell() : double |

**Figure 50 GenerationUnit class in EMMEV presented in UML**

## A2.2 Agent

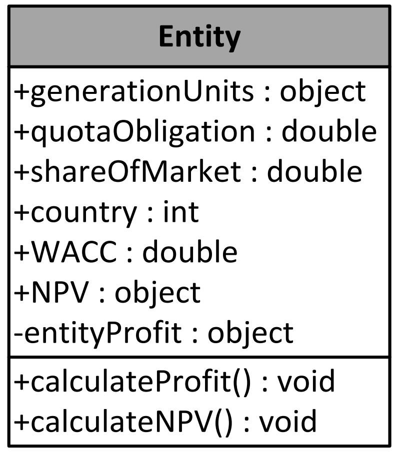


**Figure 51 Entity class in EMMEV represented in UML**

## A2.3 RunEMMEV

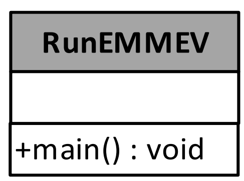


**Figure 52 RunEMMEV class in presented in UML**

## A2.4 GlobalPlanner

| **GlobalPlanner** |
|---|
| +nYears : int<br>+currentYear : int<br>+startYear : int<br>+endOfHorizonYear : int<br>+entities : object |
| +compileYearSettings() : void<br>+createEntities() : void<br>+getQuotaObligation() : double<br>+increaseYear() : void<br>+getCurrentYear() : int<br>+getNumberOfYears() : int |

**Figure 53 GlobalPlanner class in EMMEV presented in UML**

## A2.5 Market

| **Market** |
|---|
| +totalCertificate : double<br>+remainingCertificates : double<br>+remainingQuotas : object<br>+remainingCertificatesCurve : object<br>+electricityPricesMap : object<br>+marketOutputMap : object |
| +determineCertificatePrices() : void<br>+getElectricityPrice() : double |

**Figure 54 Market class in EMMEV presented in UML**

## A2.6 MarketOutput

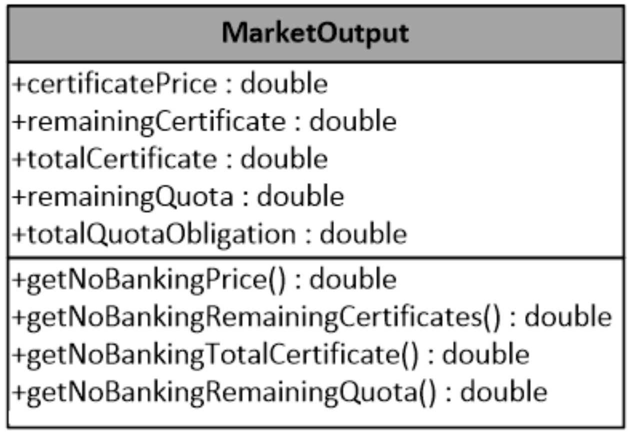


**Figure 55 MarketOutput class in EMMEV presented in UML**

## A2.7 BankingPlanner

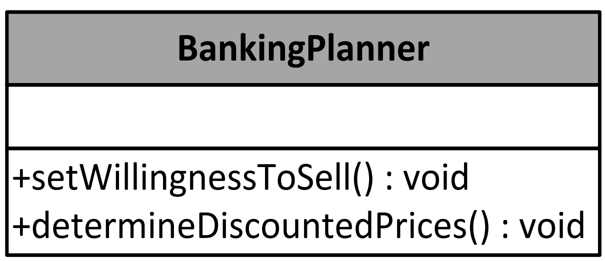


**Figure 56 BankingPlanner class in EMMEV presented in UML**

## A2.8 ExcelHandler

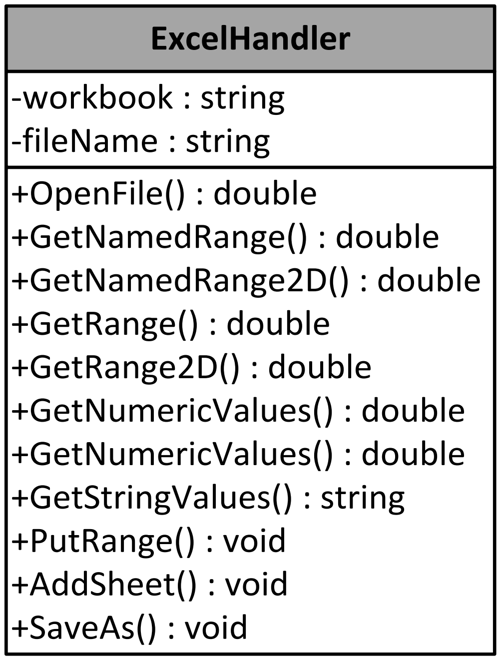


**Figure 57 ExcelHandler class in EMMEV presented in UML**

# Appendix 2
# Publications

In this section of the thesis, the publications as a result of this PhD are being described and attached to the thesis. There are two publications from this PhD work. These four publications are listed in Table 30.

**Table 30 List of main publications**

| No. | Type | Conference/Journal Name | Paper Title |
|---|---|---|---|
| Publication 1 | Conference | IEEE PowerTech 2011 | Optimal Management of Battery Charging of Electric Vehicles: A New Microgrid Feature |
| Publication 2 | Journal | MDPI – Energies 2018 | Impacts of Low-Carbon Fuel Standards in Transportation on the Electricity Market |
| Publication 3 | Journal | ELSEVIER – 2019 | ENERGY X.0: Future of Energy Systems |
| Publication 4 | Journal | ELSEVIER – 2019 | Organic data centers: A sustainable solution for computing facilities |

PowerTech is the IEEE PES anchor conference in Europe and has been attended by hundreds of delegates from around the world. It is an international forum for individuals working in industry and academia, to network, exchange ideas, and discuss the results of their research and development work. The conference will be the largest gathering of international researchers and practitioners working in the general area of electrical power engineering outside the USA.

Multidisciplinary Digital Publishing Institute (MDPI) is a pioneer in scholarly open access publishing since 1996. Based in Basel, Switzerland, MDPI has the mission to foster open scientific exchange in all forms, across all disciplines. MDPI has 212 diverse, peer-reviewed, open access journals are supported by over 35,500 academic editors. MDPI serves scholars from around the world to ensure the latest research is freely available and all content is distributed under a Creative Commons Attribution License (CC BY).

## Publication 1

# Optimal Management of Battery Charging of Electric Vehicles: A New Microgrid Feature

Ahmad Karnama, F. O. Resende, J. A. Peças Lopes, *Senior Member*, IEEE

*Abstract*—**Large deployment of Plug-in Hybrid Electric Vehicles (PHEVs) will put new challenges regarding the power systems operation. The MicroGrid (MG) concept can be exploited to support the progressive integration of PHEVs into the Low Voltage (LV) networks by developing smart charging strategies to manage the PHEVs batteries charging procedures in order to avoid reinforcements in the grid infrastructures. Assuming that a number of PHEVs owners allow managing the batteries charging when their cars are parked, this paper proposes an approach that aims to find suitable individual active power set-points corresponding to the hourly charging rate of each PHEV battery connected to the LV grid. The Evolutionary Particle Swarm Optimization (EPSO) tool is used to find these active power set points. This requires an additional software module to be housed in the MV/LV secondary substation level, called Optimal Power Set-points Calculator (OPSC).**

*Index Terms* — **MicroGrid, Plug-in Hybrid Electric Vehicles, Smart Charging, Evolutionary Particle Swarm Optimization, Optimal Power Set-points Calculator**

## I. Introduction

Plug-in Hybrid Electric Vehicles (PHEVs), which get their required energy from electricity and petroleum, seems to be a competitive technology with current conventional Internal Combustion Engine (ICE) based vehicles. In fact PHEVs have been promoted by politicians to reduce oil dependency, but characteristics like lower driving cost and low greenhouse gas emissions have become them increasingly popular [1], [2].

Since PHEVs will partly get their required energy from the power grid, they are considered as a new type of load with considerable charging requirements and therefore the technical impacts of progressive integration of PHEVs in system operation have to be evaluated based on planned scenarios, especially for distribution networks [3], [4]. In addition, it should be taken into account further scenarios characterized by increasing penetration levels of renewable power sources with intermittent nature, such as wind and photovoltaic generation, and also microgeneration systems connected to Low Voltage (LV) distribution grids.

The replacement of ICE based vehicles by PHEVs will also require specific local charging infrastructures. Several solutions may arise to fit different needs of PHEVs owners, namely charging stations dedicated to fleets of PHEVs, fast charging stations, battery swapping stations and domestic or public individual charging points for slower charging [5]. However, in this paper only slow charging at home and in public charging points located in residential areas and connected to the distribution LV networks is considered.

Regarding the batteries slow charging procedure, the PHEVs can be considered as simple loads when their owners simply define that batteries must be charged with a fixed rate, which corresponds to a dumb charging or as dynamic loads, if their owners define a time interval for the charging to take place, allowing some EV management structure to control the charging rate under a smart charging framework. From the grid point of view, the second approach yields more benefits since the EV management structure will control the charging process by reducing/increasing the charging rate according to the system operating conditions [5]-[7], so that charging can be distributed during valley hour periods and at times when there is large renewable power generation.

The implementation of a smart management system where the PHEVs are supposed to be connected to active LV networks with microgeneration units, involves dealing with the MicroGrid (MG) concept [8]. Thus, single phase electrical batteries belonging to EV are included on the MG through a smart power electronic interface with a specific control approach called the Vehicle Controller (VC) [9]. In charging mode, the VC will receive active power set-points from a MicroGrid Central Controller (MGCC), housed at the MV/LV secondary substation level, to charge the PHEV batteries, taking into account the LV network operating conditions.

Thus, in this work, an additional software module to be housed at the MGCC is proposed to manage the EV battery charging, the Optimal Power Set-points Calculator (OPSC). Based on several variables like the batteries technology, the PHEVs owners' behavior, the mobility patterns, the places where cars are parked and the time period that they are connected to the network, the OPSC is responsible to perform an optimization procedure to determine the best hourly active power set points, corresponding to the individual charging rate of the PHEV batteries connected to the considered LV distribution grid, taking into account the corresponding load diagram and the local generation availability.

This problem has combinatorial characteristics due to the possibilities of having different and discrete active power set-points. So, the Evolutionary Particle Swarm Optimization (EPSO) [9] tool was used for that purpose.

This work was supported by Fundo de Apoio à Inovação (FAI) under the framework of the Project REIVE-Redes Eléctricas Inteligentes com Veículos Eléctricos (Smartgrids with Electric Vehicles).

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## II. The MG Architecture with PHEVs

A MG is a LV distribution system with several comprising small modular generation units connected to the LV network through power electronic interfaces, electrical loads, storage devices and a hierarchical control and management system supported by a suitable communication infrastructure, such that the MG can be operated either in islanded mode or connected to the MV system [8], [10]. The MG is centrally controlled and managed by the MGCC installed at the MV/LV secondary substation, which is responsible to head the MG hierarchical control system. For this purpose the MGCC includes several key functions that support adequate technical and economical management policies and allow providing set points to the second control level comprising Microsource Controllers (MC) and Load Controllers (LC), in order to control locally the controllable microgeneration units and the responsive loads, respectively.

Regarding the MG concept, the single-phase electrical batteries belonging to the PHEV have been included through a smart power electronic interface with a specific control approach, called the Vehicle Controller (VC) [6]. Thus, the MG architecture with PHEV connected to it is represented in Figure 1.

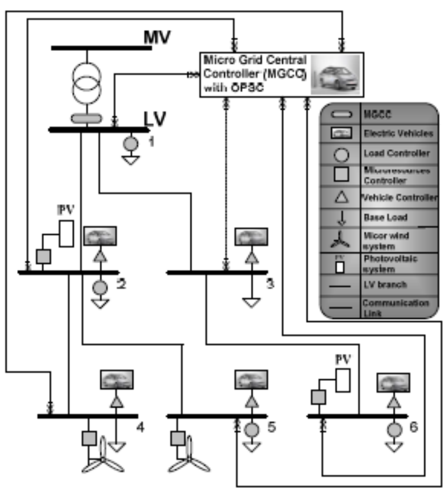


Fig. 1. The MG architecture with PHEVs

In order to assure a smart management of battery charging of PHEVs, a new feature was included on MGCC. The OPSC is then responsible to calculate the rated charging power of each PHEV battery to be sent from the MGCC to the corresponding VC. For this purpose, when each PHEV is plugged in, the corresponding VC sends to the MGCC the following information: a) the battery capacity and technology, b) the battery initial state of charge, c) the expected PHEV parking duration and d) the battery desired final state of charge. Based on this information and considering the forecasted local and daily load diagram as well as the forecasted local daily production from microgeneration systems, the OPSC performs an EPSO-based optimization procedure in order to find the best hourly battery charging rates for the 24 hours.

## III. The OPSC Optimization Problem

For a given LV distribution network, beyond the data sent by VC to the MGCC, described in the previous section, the initial data of the OPSC optimization problem includes also the area mobility pattern given by the expected number of PHEVs that will plug-in in each hour according to the human behavior of the corresponding area. The solution of the hourly active power set points corresponding to the individual charging rates of PHEVs can be obtained by solving an optimization problem that involves the minimization of the variance of the active power flow through the MV/LV substation considering the additional consumption of the PHEV batteries. This has been first introduced in [4] and was adopted in this work aiming to improve the system operating conditions through the PHEV additional load transfer from the peak hours to the valley hours and to the periods corresponding to high local generation levels.

Mathematically, the problem can be formulated as:

$$\min \left(\sum_{h=1}^{24} \frac{(P_h - \mu)^2}{24}\right) \tag{1}$$

where $P_h$ is hourly injected active power considering the PHEVs consumption and $\mu$ is the average value of active power after adding PHEVs consumption, which are derived as in equation (2) and (3), respectively.

$$P_h = P_{MG} - P_{base} - P_{PHEV} \tag{2}$$

$$\mu = \frac{\sum_{h=1}^{24} P_h}{24} \tag{3}$$

In equation (2), $P_{MG}$, $P_{base}$ and $P_{PHEV}$ are the PHEVs active power, the base regular load diagram and the microgeneration levels during 24 hours of a typical day.

However, the objective function given by equation (1) is subjected to the following technical constraints:

$$V_{min} < V_i < V_{max} \qquad i = 1 \dots n \tag{4}$$

$$LFSOC_j < OFSOC_j < HFSOC_j \qquad j = 1 \dots p \tag{5}$$

$$I_k < I_{k\,max} \qquad k = 1 \dots l \tag{6}$$

Indicators $i$ and $j$ shows the order of each bus bars and the order of each PHEV, respectively, being $n$ the number of buses and $p$ the number of plugged-in PHEVs. $V_i$ shows the voltage in each bus bar and $V_{min}$ and $V_{max}$ represent, respectively, its minimum and maximum values (0.9 and 1.1 p.u). Moreover, *LFSOC*, *HFSOC* and *OFSOC* shows the lowest desired, highest desired and optimal state of charge of the battery while the first and second are input values stated by the car driver and the last value is the output of the optimization problem. Finally, $I_k$ and $I_{k\ max}$ are the current in line k and the corresponding maximum limit, respectively, being $l$ the number of lines in the network.

## IV. Using EPSO to implement the OPSC

EPSO was adopted to find good solutions for the optimization problem described in section III. This approach is a powerful optimization methaeuristic particularly well suited to deal with combinatorial problems with a large number of possible solutions, like this one, where discrete variables are used [9]. However, the adoption of this procedure demands the following main stages:

- A suitable codification of each potential solution - the definition of the particle object parameters;
- The definition of a suitable fitness function in order to represent the quality of each solution, expressed in terms of the load curve variance according to equation (1);
- The use of the EPSO procedure.

### A. *Particle definition*

EPSO is a population based optimization algorithm. At a given generation, the set of potential solutions for the problem to be solved is called a set of particles or swarm. Each particle comprises two sets of parameters, the strategy parameters and the object parameters, corresponding respectively to the weights that govern the movement rule and to the particle position into the search space. Since EPSO is a self adaptive method, benefiting from the evolutionary process to progressively adapt the parameters that guide its own search, the particle definition involves only the specification of the object parameters [9].

Under the framework of the OPSC optimization problem to be solved, the potential solutions involve the active power set points for each PHEV at each hour, corresponding to hourly charging rates for each battery, as stated before. Therefore, the size of set of object parameters is $p \times 24$, where p is the number of PHEVs. Figure 4 shows the structure of the object parameters of the particle.

| Hour 1 | | | | Hour 2 | | | | … | Hour 24 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $P_1$ | $P_2$ | … | $P_p$ | $P_1$ | $P_2$ | … | $P_p$ | … | $P_1$ | $P_2$ | … | $P_p$ |

Fig. 2 Structure of the particle object parameters

### B. *Evaluation function*

The problem of minimizing the objective function described by equation (1), when subjected to the constrains identified, can be treated in terms of fitness function as

$$FIT = \sum_{h=1}^{24} \frac{(P_h - \mu)^2}{24} + P \tag{7}$$

The term P represents the particle penalty when the required state of charge of the batteries is not achieved and is determined as:

$$P = P_1 + P_2 = \left( \sum_{j=1}^{p} P_{1j} + \sum_{j=1}^{p} P_{2j} \right) \times 10^5 \tag{8}$$

where

$$P_{1j} = \begin{cases} (OFSOC_j - HFSOC_j) \times BC_j & OFSOC_j > HFSOC_j \\ 0 & else \end{cases} \tag{9}$$

$$P_{2j} = \begin{cases} (LFSOC_j - OFSOC_j) \times BC_j & OFSOC_j < LFSOC_j \\ 0 & esle \end{cases} \tag{10}$$

The index j accounts for the PHEV number and BC is the battery capacity.

The technical constrains regarding both bus voltage profile and thermal limits of branches are only considered in the next stage.

### C. *The EPSO based optimization procedure*

The approach starts with the search space definition through the specification of both the minimum and maximum values of each object parameter of the particle. For this purpose, it was assumed that the minimum values of the active power set-points are set to zero, meaning that although the PHEVs are plugged-in their batteries are not in charging mode. Regarding the maximum values of the active power set-points, it was assumed that they correspond to the maximum charging rate of the PHEV batteries, meaning that when no technical constrains arise concerning the grid operation the PHEVs batteries will charge according its nominal charging rate.

After defining the search space, it is expected that the EPSO algorithm will find the best solution or, at least, a good solution in the sense of the fitness function. For this purpose, the usual EPSO operators (replication, mutation and selection) are used and the following sequence of steps has to be carried out for each particle in the swarm [9]:

1. Perform replication;
2. Perform mutation of the particle strategy parameters;
3. Perform recombination according to the movement rule;
4. Perform the evaluation function;
5. Perform selection.

In this work it was used an EPSO algorithm with 20 particles in the swarm, replication factor $r=1$ (each parent gives birth to one descendant) and Gaussian mutation with learning rate $\tau$=0,5. The stopping criterion is the maximum number of iterations, which was assumed to be 1500. These parameter values were adopted based on the experience in using EPSO to deal with this problem.

After performing the EPSO algorithm, the best particle to be found, which corresponds to the lowest value of the fitness function, should respect the technical constrains regarding the voltage profile of each bus and the thermal limits of LV branches, according to equations (4) and (6), respectively. Thus, in order to check these technical constrains, an unbalanced three-phase load flow tool [11] was used. In case of these constrains are not verified, due to branches congestion problems or bus voltage profiles too low, the upper limits of the search space are decreased and the EPSO algorithm will be ran again.

The approach algorithm is shown graphically by means of the flow chart depicted in Figure 5.

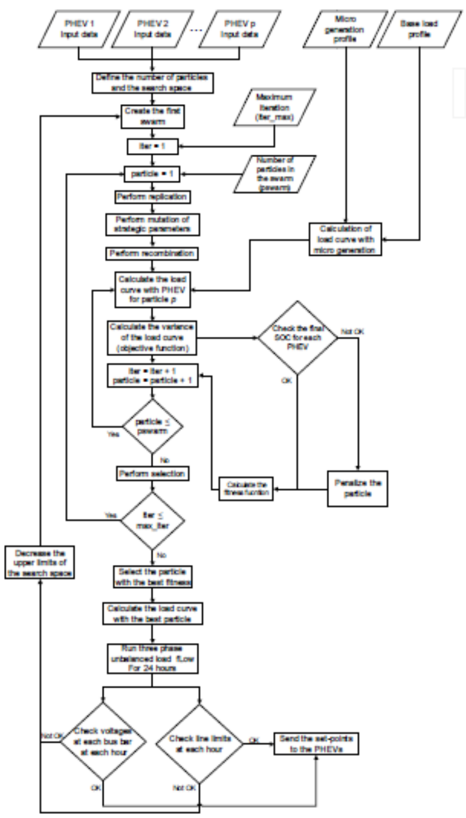


Fig. 5 The EPSO based OPSC approach

## V. Test System

In order to assess the performance of the approach described above, the 24-bus bar LV distribution network presented in Figure 6 was used. It corresponds to a typical rural, 400 V grid, fed by a 50 kVA upstream transformer. This is a fairly weak residential network, comprising mainly single-phase loads. However a few three-phase loads are also connected to this network. In this test system, it was assumed that there are microgeneration systems, both wind and Photovoltaic (PV).

Due to the common lack of typical LV network full characterization, it was assumed that the individual base loads are homothetic, being thus obtained from the LV network typical base load diagram presented in figure 7, according to the corresponding contracted power and taking into account a suitable LV network simultaneity factor for the peak hour. It should also be noted that the single-phase loads were distributed among the different phases trying to minimize the load unbalance.

It was also assumed that the microgeneration systems, both wind and PV, are only connected to the load buses. Taking into account that all the micro wind and PV systems are subjected to the same wind and solar conditions, respectively, they follow the same generation profiles. For a typical summer day, both wind and PV profiles are presented in figure 8 in terms of the percentages of the corresponding installed capacities.

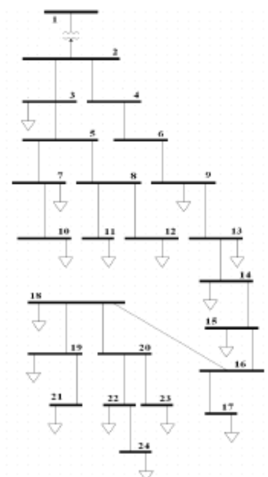


Fig. 6 The 24-bus bar LV distribution network

In order to perform a 24 hour simulation, a typical daily load diagram was used, as depicted in figure 7, corresponding to a typical summer day.

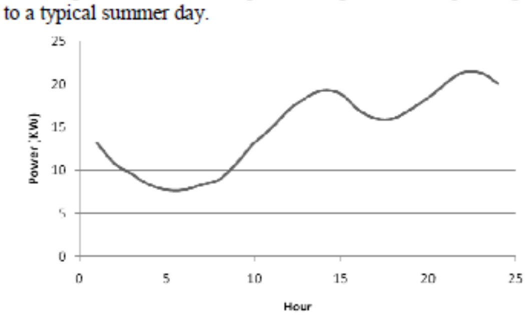


Fig. 7 The load diagram during a typical summer day

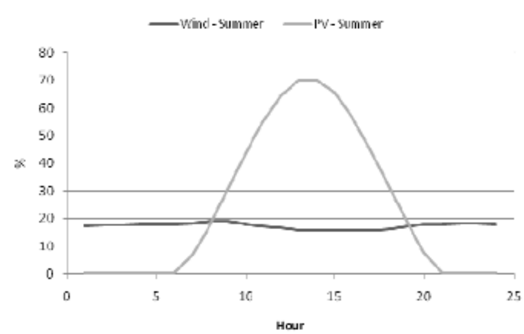


Fig.8 Microgeneration profiles (percentage of the installed capacity)

The installed capacities of both micro wind and PV systems were determined based on the following assumptions:

1. The total installed capacity of the LV network is less than a quarter of the upstream transformer rating (in this case less than 12,5 kW);
2. For each load bus, the installed capacity of maicrogeneration systems is one half of the corresponding contracted power, being always less than 3 kW;
3. The share of the installed capacity is 80% for PV systems and 20% for micro wind systems.

In order to fully describe the adopted test system, it is necessary to determine the number of PHEVs, which is usually estimated as a percentage of the total number of cars in the area. For this purpose, it was assumed that the LV network presented in figure 6 provides electricity for 50 people and in average each 3 people have 2 cars in that area. Based on these assumptions and using the methodology presented in [4], it was estimated that 16% of the ICE-based cars will convert to PHEVs, meaning that 8 PHEVs will plug-in in this LV network. However, this is a future scenario corresponding to the year 2022. Therefore, the base load diagram presented in figure 7 was updated in order to include the yearly rate of load increase. For this purpose it was assumed a 0.5% of yearly load increasing.

The PHEVs are connected to the several bus bars and in different phases as described in Table I.

TABLE I Connection of PHEVs to the grid

| *PHEV no.* | *Bus bar* | *1 or 3 phase* | *Phase* |
|---|---|---|---|
| 1 | 3 | 1 | 1 |
| 2 | 7 | 1 | 2 |
| 3 | 9 | 1 | 3 |
| 4 | 10 | 1 | 1 |
| 5 | 11 | 1 | 3 |
| 6 | 11 | 1 | 1 |
| 7 | 12 | 3 | - |
| 8 | 13 | 3 | - |

Since the base load connected to bus 12 and bus 13 is a three-phase load it was assumed a three-phase connection regarding PHEV 7 and PHEV 8. This PHEV distribution follows a connection strategy corresponding to the best case scenario from the grid operation perspective. This is due to the fact that the PHEVs are connected to the bus bars nearest the upstream transformer, meaning that better voltage profiles are expected as well as lower levels of branches congestions. The worst case scenario corresponds to a situation where the PHEVs are connected to bus bars located farthest from the transformer. However, this case scenario was not investigated in this study.

## VI. Simulation Results and Discussions

The developed approach has been tested using the test system presented in section V, considering the PHEVs specifications presented in Table II.

The considered PHEV fleet includes cars with different rated power according to the battery capacity [12], intended to face different owners needs in terms of driving ranges. The average charging time of each PHEV was assumed to be 4 hours at their rated power. Regarding the starting time specified in Table II, it was assumed that PHEVs owners plug-in their cars when they arrive from the last journey, using domestic charging points. This mobility pattern is based on the results presented in [13] for Portugal.

TABLE II Detailed information about PHEVs

| *PHEV no.* | *Battery capacity (kWh)* | *Charging rate (kW)* | *Starting time* | *Parking Duration* | *State of Charge (%)* | | |
|---|---|---|---|---|---|---|---|
| | | | | | *Primary* | *Min final* | *Max final* |
| 1 | 8 | 2 | 17:00 | 8 | 10 | 70 | 100 |
| 2 | 8 | 2 | 17:00 | 8 | 10 | 70 | 100 |
| 3 | 8 | 2 | 18:00 | 12 | 10 | 70 | 100 |
| 4 | 8 | 2 | 19:00 | 12 | 10 | 70 | 100 |
| 5 | 10 | 2,5 | 20:00 | 10 | 15 | 75 | 100 |
| 6 | 10 | 2,5 | 20:00 | 11 | 15 | 75 | 100 |
| 7 | 15 | 3 | 20:00 | 24 | 20 | 80 | 100 |
| 8 | 15 | 3 | 22:00 | 24 | 20 | 80 | 100 |

As stated in section II, when the PHEVs are connected to charge their batteries, the car driver provides information about the parking duration in order to allow the management of the battery charging according to the specified final state of charge and taking into account the initial state of charge. So, this data is also included in Table II.

In order to demonstrate the performance of OPSC approach, four case studies were planned, as summarized in table III, aiming to compare the effects on the system operation resulting from using the OPSC based smart charging strategy and a dumb charging strategy. These effects were also compared considering the LV network with microgeneration and without microgeneration.

TABLE III Case studies

| *Case study* | *Microgeneration* | *Smart / Dumb charging* |
|---|---|---|
| A | No | Dumb |
| B | Yes | Dumb |
| C | No | Smart |
| D | Yes | Smart |

It should be noted that when a dumb charging approach is used PHEVs owners are completely free to connect and charge their vehicles after parking without any kind of charging control. The charging starts automatically when PHEVs plug-in and lasts for the next four hours with the charging rate specified in Table II.

### *A. Dumb charging results without micro generation*

Since all the PHEV owners charge their vehicles when they arrive home from the last journey of the day, this procedure provokes an increase in load consumption that lasts for four hours, as it can be observed from figure 9.

Moreover, the high consumption of PHEVs happens at peak hours (in the evening) leading with a considerable increase in the total peak power. The additional load of PHEVs, in this week rural LV network, brings some grid operation problems, such as branches congestions and large voltage drops. Problems of convergence were verified when performing the 24-hour load flow analysis during the peak hours. This fact stresses the need of either to reinforce the grid infrastructures or to adopt a smart charging strategy in order to transfer the PHEVs load from the peak hours to the valley hours.

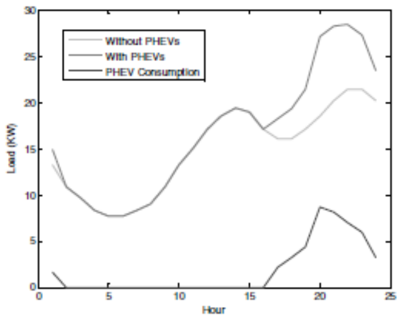


Fig. 9 LV grid load diagram for dumb charging without microgeneration

*B. Dumb charging results with micro generation*

Considering the availability of microgeneration systems, both wind and PV, with the corresponding generation profiles presented in figure 8, the resulting LV grid load diagram is presented in figure 10.

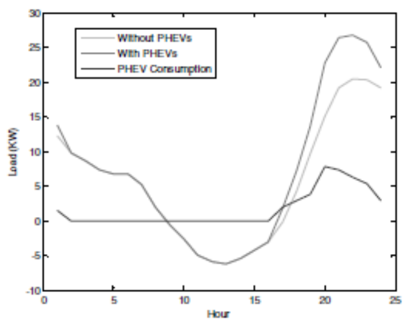


Fig. 10 LV grid load diagram for dumb charging with microgeneration

As it can be observed from figure 10, the local generation provided by both micro wind and PV systems does not affect significantly the load diagram during the peak hours and a similar peak power increasing was verified when comparing figure 10 with figure 9.

During the period corresponding to the PV systems generation, as the PHEV consumption is zero, the LV network is exporting power to the upstream MV network. So, it will be interesting to move the additional PHEV load from the peak hours to this period, if PHEVs are parked, exploiting the OPSC based smart charging strategy.

*C. Smart charging without micro generation*

The OPSC based smart charging strategy was applied to find suitable active power set-points in order to manage the charging process of the PHEV batteries, according to both the parking duration and minimum final state of charge, which are specified in Table II, trying to minimize the negative impacts regarding the network operating conditions. For this purpose, the search space was defined, as already mentioned previously, being the lower limits set to zero and the upper limits set to the charging rates of each PHEV battery described in table III. It should be noted that the set of the particle object parameters comprises 192 active power set-points and the required computation time was around 200 seconds.

Considering the LV test system without microgeneration and after performing the EPSO-based OPSC approach, the obtained hourly active power set-points corresponding to the battery charging rates are presented in the figure 11.

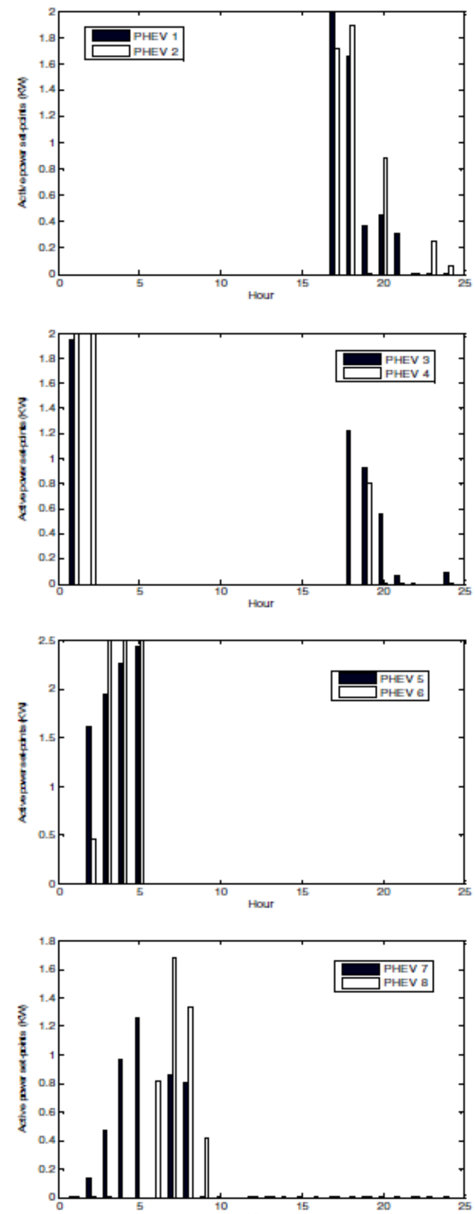


Fig. 11 Hourly active power set-points for each PHEV

As it can be observed from figure 11, all the PHEVs charge their batteries with an hourly variable charging rate. However, the minimum state of charge specified by the PHEVs owners was achieved for all the cars without grid operation problems.

Regarding PHEVs number 1 and 2, although they are parked between 17h00 and 23h00, they are almost charged before 20h00 in order to avoid additional load during the peak hours. In case of PHEV 3 the battery load is partially transferred to the valley hours. On the other hand, as the remaining PHEVs are parked during the night, their batteries are fully charged during the valley hours. It should also be noted that the batteries of PHEVs number 5 and 6 are charged latter than these ones of PHEVs 7 and 8. This is due to the fact that, in the last case, the charging duration was extended. However, although these two PHEVs can be charged freely during 24 hours, the preferred period relies on the valley hours.

As a result of the application of the OPSC based smart charging strategy, the LV network daily load diagram was modified, as it can be observed in figure 12.

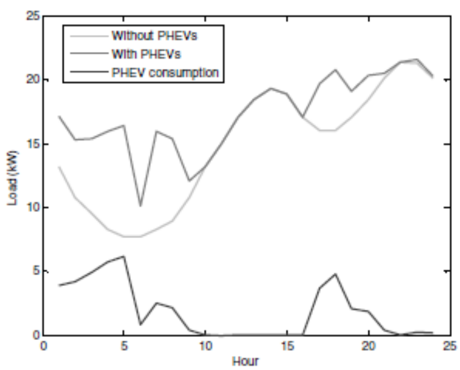


Fig. 12 LV grid load diagram for smart charging without microgeneration

When compared with the load diagram presented in figure 9, which corresponds to the dumb charging strategy, the load curve is flatter because an amount of the additional PHEV load was shifted from the peak hours to the valley hours.

### D. *Smart charging with micro generation*

In this case study it was considered the presence of microgeneration systems, both micro wind and PV systems, in the test system LV network. The proposed OPSC based smart charging approach was then applied considering the specifications presented in Table II and the same conditions of case study C, regarding the search space definition and the particle size (the set of object parameters). The required computation time was around 200 seconds. The obtained hourly active power set points that define the battery charging rates are presented in figure 13.

When compared with the results of case study C, in particular these ones presented in figure 11, the battery load corresponding to PHEVs number 7 and 8 was transferred to the period when PV systems are generating active power, being the peak of generation during noon hours, as it can be observed from figure 8.

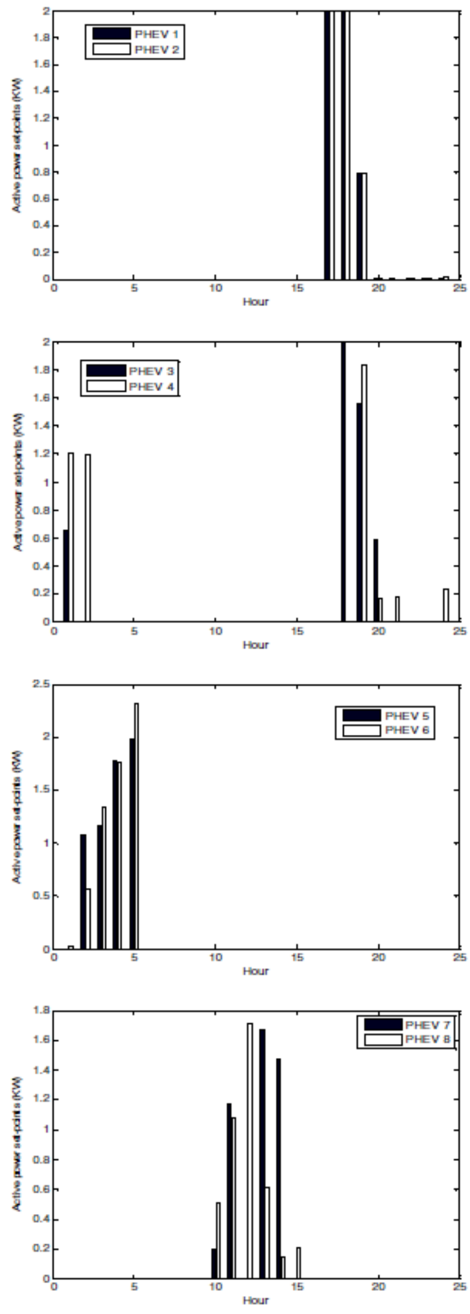


Fig. 13 Hourly active power set-points for each PHEV

Following the PHEVs battery charging management based on the individual charging rates presented in figure 13, the LV network daily load diagram was modified, as it can be observed from figure 14.

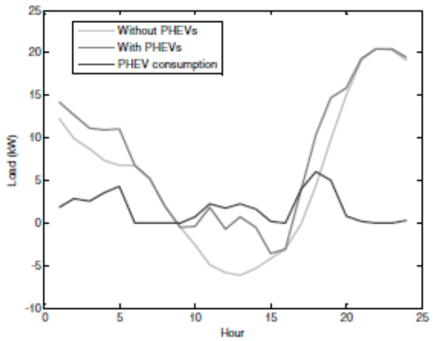


Fig. 14 LV grid load diagram for smart charging with microgeneration

## VII. Conclusions

Large deployment of PHEVs will impose new challenges to power systems operation, in particular, to LV distribution networks, requiring thus the development of adequate technical management structures to deal with smart charging schemes in order to reduce the negative impacts of PHEVs integration trying to avoid reinforcements in the grid infrastructures. In this context, an OPSC based smart charging strategy was proposed in order to deal with PHEVs battery management in LV networks, being this software module housed in the MGCC.

The performance of the proposed approach was evaluated considering a typical LV distribution network integrating simultaneously microgeneration systems (wind and PV) and PHEVs. The results obtained allow concluding about the effectiveness and robustness of the developed approach to find hourly active power set points to charge each PHEV battery when PHEVs are parked. This charging scheme allows operating the LV networks in less stressed conditions.

Further developments include the enhancement and adaptation of the OPSC based smart charging approach to deal with this problem in real time applications.

## VIII. Acknowledgments

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## IX. References

[1] M. Kinter-Meyer, K. Schneider, R. Pratt, "Impacts assessment of plug-in hybrid electric vehicles on electric utilities and regional U.S. power grids. Part I-Technical analysis", Pacific North West National Lab., Richland, WA, PNNL-SA-61669, Jan. 2007.

[2] EPRI & NRDC Environmental assessment of plug-in hybrid electric vehicles. Volume 1: Nationwide greenhouse gas emissions, Final Report 1015 325, Jul. 2007.

[3] K. Clement, E. Haesen, J. Driesen,"Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids," in *Power Systems Conference and Exposition, 2009. PSCE '09. IEEE/PES*, 2009, pp. 1-7.

[4] A. Karnama and V. Knazkins, "Scenario-based investigation of the effects of Plug-in Hybrid Electric Vehicles (PHEVs) in 11 kV substations in Stockholm," in *Energy Market (EEM), 2010 7th International Conference on the European*, 2010, pp. 1-6.

[5] J. A. Peças Lopes, F. J. Soares, P. M. R. Almeida, "Integration of electric vehicles in the electric power system", Proceedings of the IEEE, Vol. 99, Nº 1, January 2011, pp. 168-183

[6] J. A. P. Lopes, F. J. Soares, P. M. R. Almeida, "Identifying management procedures to deal with connection of Electric Vehicles in the grid," in *PowerTech, 2009 IEEE Bucharest*, 2009, pp. 1-8.

[7] J. A. Peças Lopes, F. J. Soares, P. M. R. Almeida, A. M. M. da Silva, "Smart charging strategies for electric vehicles: Enhancing grid performanceand maximizing the use of variable renewable energy sources", in Proc. 24th Int. Battery Hybrid Fuel Cell Electric Vehicle Sym. Exhib., Stavanger, Norway, 2009, pp. 1.11

[8] J. A. Peças Lopes, S. A. Polenz, C. L. Moreira, R.Cherkaoui, "Identification of control and management strategies for LV unbalanced microgrids with plugged-in electric vehicles," *Electric Power Systems Research*, vol. 80, 2010, pp. 898-906.

[9] V. Miranda, "Evolutionary algorithms with particle swarm movements", Proceedings of 13th International Conference on Intelligent Systems Applications to Power Systems,2006, pp. 6-21.

[10] J. A. Peças Lopes, C. L. Moreira, A. G. Madureira, "Defining control strategies for microgrids islanded operation", IEEE Transactions on Power Systems, vol. 21, 2006, pp. 916-924.

[11] C. S. Cheng and D. Shirmohammadi, "A three-phase power flow method for real-time distribution system analysis," *Power Systems, IEEE Transactions on*, vol. 10, pp. 671-679, 1995.

[12] N. K. Robert Ball, Marcus Alexander, Ed Bower, "Modelling electric storage devices for EV", WP2 Task 2.1 Deliverable D2.1, 2010.

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## Publication 2

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# Impacts of Low-Carbon Fuel Standards in Transportation on the Electricity Market

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**Abstract:** Electric Vehicles (EVs) are increasing the interdependence of transportation policies and the electricity market dimension. In this paper, an Electricity Market Model with Electric Vehicles (EMMEV) was developed, exploiting an agent-based model that analyzes how carbon reduction policy in transportation may increase the number of Electric Vehicles and how that would influence electricity price. Agents are Energy Service Providers (ESCOs) which can distribute fuels and their objective is to maximize their profit. In this paper, the EMMEV is used to analyze the impacts of the Low-Carbon Fuel Standard (LCFS), a performance-based policy instrument, on electricity prices and EV sales volume. The agents in EMMEV are regulated parties in LCFS should meet a certain Carbon Intensity (CI) target for their distributed fuel. In case they cannot meet the target, they should buy credits to compensate for their shortfall and if they exceed it, they can sell their excess. The results, considering the assumptions and limitations of the model, show that the banking strategy of the agents contributing in the LCFS might have negative impact on penetration of EVs, unless there is a regular Credit Clearance to trade credits. It is also shown that the electricity price, as a result of implementing the LCFS and increasing number of EVs, has increased between 2% and 3% depending on banking strategy.

**Keywords:** low-carbon fuel standard; electric vehicles; policy analysis; electricity market; agent-based modelling

### 1. Introduction

The most important global agreement addressing climate change was signed in Paris in 2016 under the United Nations Framework Convention on Climate Change [1] dealing with the mitigation of Greenhouse Gas (GHG) emissions starting in the year 2020. This agreement indicates the global commitment (195 courtiers signed the Paris Agreement) to address the severe global consequences related to climate change. By means of this agreement, the global average temperature should be held below 2 °C and a pathway for GHG emissions and climate-resilient development should be designed [1].

Almost a quarter (23%) of global energy-related GHG emissions are from the transport sector [2] and it is the fastest growing sector for emissions [3]. In addition, around 35% of the fossil fuels in the world are consumed in the transport sector [4]. Therefore, design and implementation of transportation policies to decrease emissions is of high importance in order to comply with the Paris Agreement [5].

Sustainable transportation and the electrification of the transportation sector are highly interrelated and it is shown that in general, electrification of transport can lead to lower carbon emissions in transportation [6]. On the other hand, support schemes promoting different sustainable transportation are preferably to be local and based on Life Cycle Analysis (LCA). In Fazeli and Leal [7], based on LCA, it is shown that, in most of the cases, electrification of the transport sector can lead to lower carbon emissions. Based on the above studies, it is assumed in this paper that the electrification of the transport sector can lead to lower emissions.

Electric mobility support programs include policies that subsidize the higher purchase price of Electric Vehicles (EVs) and promote the installation of charging infrastructure [8,9]. These policies will eventually increase the number of EVs on the roads and increase electricity consumption [10,11] and will impact electricity markets as single platforms for electricity trade. This research contributes to the field by increasing the understanding of the intersection between electric mobility programs and the electricity market.

The main objective of this paper is, therefore, to bring understanding on how Low-Carbon Fuel Standard (LCFS), a performance-based policy instrument to accelerate transition to low-carbon fuel in transportation, can influence the structure and prices of the electricity market as well as EV sales. This is performed by modelling LCFS and the electricity market, and the hypothesis of the model is that sustainable transportation support polices will increase the number of electric vehicles and this will increase demand for electricity, which is expected to increase the electricity price [12].

EMMEV stands for Electricity Market Model with Electric Vehicles and, under the framework of this research, is an agent-based model developed by the authors to study the above research questions. In this paper, Electric Vehicles refer to vehicles with grid charging capability including Plug-in Hybrid Electric Vehicles and Battery Electric Vehicles. EMMEV is a platform that allows the testing of different policies for increasing the number of Electric Vehicles and charging infrastructure. Throughout this paper, the LCFS is chosen as a low-carbon transportation support policy in order to investigate the impact on electricity price and EV sales.

The Low-Carbon Fuel Standard (LCFS) [13] is one of the regulatory measures for increasing the share of low-carbon fuels in the transportation sector. The LCFS regulates the fossil carbon content of different fuels to reduce carbon emissions. It is a performance-based policy which aims to decrease the CI (Carbon Intensity) of transportation fuels. This has been implemented in California. For a description and discussion of its implementation, please see Farrell and Sperling [14] and Yeh, Sperling [13].

In this paper, first, the main concepts related to EMMEV are described. Thereafter, the structure of EMMEV is explained. A test system for testing the impact of the LCFS on the electricity market is introduced in Section 4. The results and discussions are presented in Section 5. Finally, in Section 6, a summary and conclusions are presented.

## 2. Background and Review of Relevant Concepts

The Electricity Market with Electric Vehicles (EMMEV) consists of two submodels. The first submodel is the electricity market model and the second is a model for the Low-Carbon Fuel Standard. In this section, the two submodels are described.

### 2.1. Electricity Market

Electricity is a commodity that does not behave like regular commodities [15]. The first difference is, unlike other commodities, electricity cannot be stored and needs to be consumed as it is produced. Secondly, the supply at each time needs to exactly meet the demand. The third difference is that the (relatively small-scale) storage capability and transfer of electricity is subject to major losses. All above-mentioned differences have made the structure of the electricity market unique, since traders cannot store a large percentage of the commodity.

There is a fourth difference which makes the trading structure of electricity even more unique: electricity is becoming a dominant energy carrier and is entering other energy sectors such as transportation [16]. Thus, there might be mutual influences between the electricity market structure and transportation policies.

An electricity market is a market for trading electricity and related services. The market is mainly cleared at partial time spans (usually one hour) and all the agents participating in the market are subjected to the same price (the pool price) unless the agents have bilateral contracts. The regulated parties in the market are generation units, which need to bid into the market the amount of energy that they can generate for each hour and the corresponding prices per unit of energy. On the other hand, there are retailers who buy electricity on an hourly basis. The demand is usually quite inelastic, however, new regulations and products (such as load disaggregation products such as Bidgley [17]) are designed to increase the responsiveness and bring flexibility to the demand side [18].

In order to guarantee a secure supply of electricity, there are three markets with different time regimes within the electricity market: the spot market, power regulation, and the automatic reserve [19]. The spot market (also called load settlement) is an hourly price settlement which leads to a uniform price for all regulated parties in a specific area. The additional balancing requirements which cannot be met in the spot market, due to unexpected demand changes within an hour, are regulated in the power regulation market. This occurs within minutes or seconds. The automatic reserve serves the need to balance the demand and supply within fractions of a second. There are some generation units with very fast response times which can enter this mode and balance the load very quickly [18,19] . In this paper, the spot market of the electricity market is modelled in the first submodel within EMMEV.

### 2.2. *Low Carbon Fuel Standard*

The transition to low-carbon transportation fuels is becoming increasingly important and needs a fast change. However, introduction of low-carbon fuels in transportation is hindered by limitations and problems including reduced investments, barriers in technology development and energy industries [20], other forms of technological and market inertia delaying investments in deployment and Research and Development (R&D) [21], cartel pricing, and the failure of markets to assign a price to greenhouse gas (GHG) emissions [13].

Various policies are adopted to overcome these market failures and barriers, ranging from regulatory measures, such as emissions regulations and fuel economy standards, to financial levers such as tax reductions, rebates, and feebate schemes [22]. There are other policies, such as waivers for parking places and tolls, and specifying separate driving lanes for EV drivers. Each has different advantages and disadvantages [23,24].

Among the regulatory measures, the LCFS is a performance-based policy designed to accelerate the transition to low-carbon transportation fuels by stimulating innovation and investment in new fuels and technologies. The LCFS aims to provide a durable policy framework that will stimulate innovation and technological development. Since 2007, the LCFS policy has been adopted in California, Oregon, the European Union (Fuel Quality Directive, FQD), and British Columbia (Renewable and Low-Carbon Fuel Requirement Regulation, RLCFRR) [25–27].

The LCFS is based on credit trading, with the intent of harnessing market forces and providing industry with flexibility to optimize their incentives. To assure that emissions are regulated effectively, life-cycle measurements of GHG emissions are used.

The LCFS is a hybrid of a regulatory and market policy instrument. It does not include mandates for any fuel or technology and as such does not attempt to pick winners or losers. Instead, it defines an average emissions intensity standard—measured in grams $CO_2$ equivalent per megajoule of fuel energy ($gCO_2e/MJ$)—that all energy providers must achieve across all fuels they provide. Many options exist for meeting the standard. Regulated parties are free to employ any combination of strategies that suits their circumstances and perspectives, including the purchase of credits from other companies.

There is an instrument similar to the LCFS concerning renewable electricity generation called the Renewables Certificate Market (RCM). RCM was implemented in 2002 through the RPS (Renewable Portfolio Standard) in California [28] as well as in Sweden in 2003 called "elcertifikatmarknad". Norway joined Sweden in 2012 and they created the "nordiska elcertifikatmarknad" [29]. The main goal of this market is to promote electricity generation from renewable resources [30,31]. RCM has been compared with the LCFS in Table 1.

**Table 1.** Comparison of LCFS and Renewables Certificate Market.

| Market | Main Goal | Players | Certificate Receivers | Quota Obligation |
|---|---|---|---|---|
| RCM | Promote renewable electricity generation | Electricity generation units and large electricity consumers and electricity retailers | One certificate for each MWh of electricity generated from renewable resources | One quota obligation for some percentage of electricity consumption |
| LCFS | Promote low-carbon transportation fuels | Energy providers for transportation | One credit for CI reduction below decreasing annual targets | One credit for sales of fuel with higher CI than LCFS annual target |

Both the LCFS and RCM aim to reduce GHG emissions. The target of RCM is the electricity generation sector while the LCFS aims to reduce GHG emissions in the transportation sector. The regulated parties in RCM are generation units and the electricity consumers. However, in the LCFS, the regulated parties are fuel distributors in the transportation sector.

In the RCM, each regulated party can receive one certificate for each MWh of electricity generated from renewable resources. Certain electricity consumers and electricity retailers are obliged to buy certificates based on the amount of electricity they consume. In the LCFS, the regulated parties can sell more low-carbon fuels, or purchase LCFS credits from other regulated parties, low-carbon fuel producers, or other regulated parties. The LCFS defines an average emissions intensity standard that all energy providers must achieve across all fuels they provide.

### 2.2.1. Operation of Low-Carbon Fuel Standard

The compositions of the vehicle's fleet (gasoline, diesel, or electric vehicles) and how fast the market can make a transition to alternative fuels/vehicle technologies determine the market share of the fuel. The LCFS provides incentives for fuels with lower intensities, but does not guarantee a higher (or the highest) market share. In the California LCFS, the target is a 10% reduction in overall CI by 2020 [32].

In each year, the regulated parties in LCFS must meet a certain CI target for the fuel they are distributing. In case the regulated parties cannot meet their target, they need to buy credits. On the other hand, if the regulated parties exceed the target, they can sell their credits. The structure and mechanism for credit trade in LCFS is described in the next sections [33,34].

All companies which provide fuel to end users in the transportation sector can choose to be regulated parties in the LCFS. The only obligated regulated parties in the LCFS are baseline fuel producers (i.e., petroleum fuel providers). All regulated parties are indirectly mandated to reduce GHG emissions by reforming their fuel supply. In EMMEV, it is assumed that the regulated parties are biofuel providers, gasoline providers, and Energy Service Companies which provide EV aggregation services. When it comes to EV aggregation services, utilities and Energy Service Providers (ESCOs) have the same behaviors.

### 2.2.2. Calculation of Credit/Deficit

The LCFS credits are calculated based on a Low-Carbon Fuel Standard defined by regulators each year and expressed in $gCO_2e/MJ$. All the regulated parties are evaluated based on a target to be eligible to get the LCFS credits (have credit) or obliged to buy the LCFS credits (have deficit). In order to calculate the number of the LCFS credits each regulated party receives, the following steps should be followed [33]. First, the energy (MJ) of the sold transportation fuel by each regulated party is calculated. The conversion factors from liter (in case of liquid fuels) or kWh (in case of electricity fuel) are available by regulators. MJ of each fuel is calculated as following:

$$\text{Litre of sold fuel} \times \text{Energy Density (MJ/Litre)} = \text{MJ} \quad (1)$$

and for EVs:

$$\text{kWh of electricity} \times \text{Energy Density (MJ/kWh)} = \text{MJ} \quad (2)$$

In the second step, the Energy Economy Ratio (EER) is considered. The EER aims to account for differences in energy efficiency for vehicles. The EER for gasoline is 1 and 3.4 for electric vehicles, since the electric engine is more efficient than the combustion engine.

The third step is to calculate the difference between the LCFS target of each specific year and the CI of the fuel sold. If the regulated party has not met its CI target, it is producing a deficit and is obliged to buy the LCFS credit. In case of exceeding the target, the regulated party is producing credit and is eligible to receive the LCFS credit.

The fourth and last step is to convert the credit/deficit into grams of $CO_2$ equivalent. Credit/deficit are expressed in terms of greenhouse gas emissions volumes, where credits indicate the emissions saved by selling a low-carbon fuel compared to selling a fuel that exactly meets the low-carbon fuel standard for that year. The tons of $CO_2$ are calculated as following:

$$\text{MJ} \times \text{EER} \times \text{CI difference } (\text{gCO}_2\text{E/MJ}) \times 10^{-6} = \text{credit or deficit generated} \quad (3)$$

The final number shows the number of deficit/credit that each regulated party will get for the fuel sold at each year.

### 2.2.3. Electricity in the LCFS

In California, under the new regulations, new regulated parties are introduced in the market in which electricity used as a transportation fuel can generate the LCFS credits. These regulated parties are Electric Vehicle Service Providers (EVSP) for public charging, Electric Vehicle (EV) fleet operators, battery switch station owners, site hosts of private access EV charging equipment at businesses or workplace, transit agencies operating a fixed guideway system or electric buses, and the Electrical Distribution System Operators (DSO) for residential charging. These regulated parties, in general, are the ESCOs which are in charge of EVs charging and providing EV charging services [35]. Utilities and ESCOs have the same behaviors when they provide EV aggregation services.

Low-carbon fuels that meet the CI target of 2020 are exempted from the LCFS. This means that entities that are providers of these fuels do not have obligations under the LCFS and can thus choose not to join the LCFS program. However, if they decide to participate in the LCFS, they can gain the LCFS credits and trade them in the structure of the LCFS [35]. In EMMEV, it is assumed that the agents with electricity as fuel for transportation decide to participate in the LCFS.

### 2.2.4. Trading in the LCFS

At the end of a compliance period (one year for most of the LCFS programs), each regulated party must retire a sufficient number of credits to meet the obligation of the compliance period. The regulator normally sets a maximum price at the beginning of each year ($200 for each credit in California) [34]. The regulated parties in the LCFS can trade their LCFS credits in one of the following markets:

- Ongoing LCFS Credit Market
- Credit Clearance Market

In the ongoing LCFS Credit Market, the regulated parties can trade their credits through bilateral contracts any time during the compliance period. This is similar to a forward contract in the electricity market [36]. There is normally a low risk in those contracts.

If the regulated parties do not have contracts in the ongoing LCFS Credit Market or there are overall credit shortfalls and the regulated parties reported net credit deficits at the end of the reporting period, the regulator will set up a clearance market to enforce the selling and trading of credits for regulated parties. Credits acquired for this purpose are defined as "Clearance Market" credits [34,35]. The Credit Clearance Market does not happen frequently; if all parties are complying, there is no need for it.

## 3. What is EMMEV?

The EMMEV is an agent-based model platform developed to analyze the effects of low-carbon transportation policies on the electricity market. In this paper, EMMEV is used to study the effects of the LCFS on the electricity market. The agents are Energy Service Companies (ESCOs) and it is assumed that the ESCOs in EMMEV can provide power generation, electricity retailing, and EV aggregation as energy services. When it comes to EV aggregation services and retailing, utilities and ESCOs have the same behaviors. Regarding power generation, there are exception cases where ESCOs own small power generation units but utilities are the ones which can own and operate larger generation units. ESCOs in this research are the mother company in which all the businesses (retail, generation, or EV aggregation) are performed in separate companies due to unbundling. This happens in reality when holding companies such as German utility (E.ON) or Energias de Portugal (EDP) perform all the activities.

### 3.1. About Modelling

Modelling is the art of simplification to describe a limited part of our complex nature (or a socio-technical system). Models support researchers and generally human beings to overcome our limited success in understanding our complex nature.

Relative to humans' understanding, nature is extremely complex. This complexity is known to human beings from very early ages. Therefore, there is no other way than relying on modelling to study the incidents in nature. This is done in two ways: statistics or dynamics [37].

Statistics is well established for modelling, while dynamics for modelling, despite its older history, is less mature regarding model development, since it requires more computational capability that has only more recently been available [37,38]. In this paper, a socio-technical system in the intersection of the LCFS and electricity market is modelled using agent-based modelling (to be described in the next section).

### 3.2. Agent-Based Modelling

The modeling tool used in this paper is an agent-based model (ABM) [39,40]. An ABM is composed of several agents. The agents can have the inherent properties of flexible autonomy, reactivity, proactiveness, and social ability [41,42].

ABM can be considered under the more generic terms of Multi Agent Systems (MAS) which simply describe various computational instruments following an agent-based approach [42]. MAS comprises also the domain of (distributed) artificial intelligence and agent-based control systems which aim to design autonomous (software) agents and implement them in real-world cases (in the sense of designing and configuring systems in practice). In contrast, ABM specifically deals with the computational representation of Complex Adaptive Systems within their boundaries. ABM is also used for studying economically motivated relationships also known as agent-based computational economics (ACE) [40], which is the main focus in this paper.

### 3.3. EMMEV: An Agent-Based Model

As mentioned above, EMMEV consists of two submodels: the electricity market model and the Low-Carbon Fuel Standard model. There are two layers in the model: the agent layer, which is the core of the modelling, and a geographical layer, which addresses different geographical locations for different case studies. EMMEV studies the interactions of agents for 15 consecutive years (2016–2030). Regardless of all the number of languages, frameworks, developed environments, and platforms published during the last decade in the literature, implementing agent-based modelling is still a complex task, which, in general, is coded by using middleware as RePast [43]. The RePast system is a Java-based middleware for the development of trivial agent platforms and agent models. It was developed at the University of Chicago's Social Science Research Computing division and is derived from the Swarm simulation toolkit. RePast offers a set of reusable Java Bean components, along with several flexible interconnection methods to combine those components, and thus create software agents. Furthermore, RePast uses the base of the Knowledge Query and Manipulation Language (KQML) to promote communications among agents inside the platform. KQML provides the basis for the most widely-used agent communication language (ACL), and over the last years it has been extended, modified, and standardized by Foundation Intelligent Physical Agents (FIPA) [44]. Agents use KQML to send performatives to indicate the action that another agent should take on its behalf. Another major meaning of the KQML is the use of ontologies to ensure that two agents communicating in the same language can correctly interpret statements in that language. The main reason for the choice of RePast is due to the Java Bean technology, which has allowed new computational features to developers to reap the benefits of rapid application development in Java by assembling predefined software components.

The agents in the model are ESCOs and they are profit-maximizing entities. The profit for each agent is calculated as below:

$$P_{ESCO} = R_{ESCO} - C_{ESCO} \tag{4}$$

The revenue of each ESCO has three sources:

$$R_{ESCO} = R_{Generation} + R_{Retailing} + R_{EV\ aggregation} + R_{LCFS} \tag{5}$$

The revenue from generation is set by the spot price of electricity and the amount of generated electricity. The revenue from retailing is also dependent on the price scheme offered to the end consumers and the amount of consumption at each hour. The EV aggregation is the revenue from the sale of electricity to EV owners. The agents can make different profits by offering different price patterns to EV owners. The ESCOs will have some revenue from the LCFS market by selling their LCFS credit. The costs associated to ESCOs are defined as the following:

$$C_{ESCO} = C_{Generation} + C_{Retailing} + C_{EV\ aggregation} + C_{LCFS} \tag{6}$$

The electricity generation costs, cost for buying electricity for retailing, and cost for buying electricity for EVs are the main costs of ESCOs. The agents are assumed to be independent entities which deal with each other under the same condition in the electricity market and the LCFS market.

It is also assumed that the agents interact with each other in a market environment based on the following four rules:

1. The agents provide the same service.
2. All agents are price takers—they cannot control the market price unless by banking strategy.
3. All agents have a relatively balanced market share.
4. Users have complete information about the service.

The agents have the possibility to bank the credits which they received from the LCFS [13]. Based on these assumptions, two scenarios are created. In the first scenario, it is assumed that all the agents are cash constrained, which means that they sell their credit by the end of each year to generate cash to operate their business. The second scenario is the case in which agent number 2 (one randomly chosen agent) banks the credits and sells them every 5 years under the assumption that they will influence the market, increase prices, and gain more profit. This might not happen in the real world with a well-functioning LCFS. However, in case the program is not well designed, then the described shortfall might occur. One of the solutions to avoid this scenario could be to define a limit on how much credits each market play can bank in each specific time or controlling credit liquidity in the market.

Agents which are eligible to receive credits in the LCFS market can sell their credits and gain some profit. In EMMEV, this profit is meant to be spent on the charging infrastructure and subsidize the sales of EVs. In Sierzchula, Bakker [9], it is claimed that each $1000 increase in financial incentives would cause a country's EV market share to increase by 0.06%. However, the investment in charging infrastructure could be more beneficial to increase the number of EVs; each additional station per 100,000 residents would increase its EV market share by 0.12% [9] and this has been used as elasticity in this research. In this paper, EMMEV is tested by assuming that the profit from the LCFS is spent in charging infrastructures. In future, EMMEV can be used to investigate different other scenarios, such as spending LCFS revenue for rebates for EVs.

In each of the three revenue cases (generation, retailing and EV aggregation, and LCFS), the agents interact differently. In Figure 1, the interaction of agents in generation is shown.

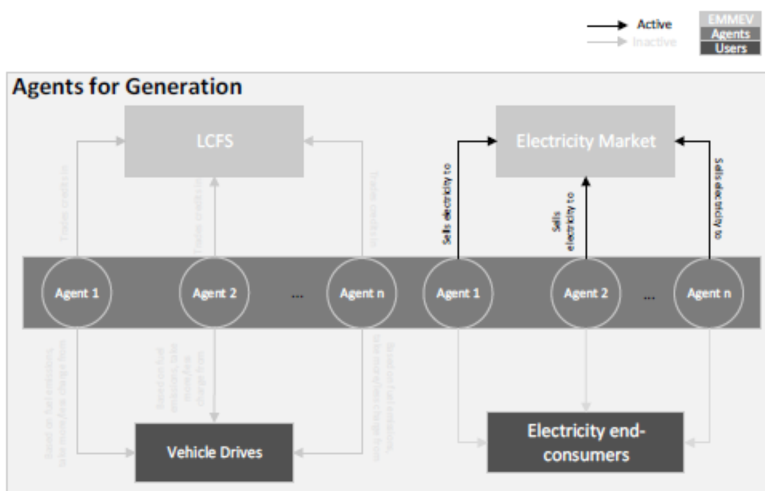


**Figure 1.** Agents interaction for generation in electricity market (only black text is relevant for this figure).

As shown in the above figure (the black lines are the focus areas and gray is not meant to be focused on and will be described in the next figures), the agents sell their generated electricity in the electricity market. It is assumed that the agents have balanced share of market and cannot influence prices. The electricity prices are set by passing the demand curve through the generation curve at each hour.

Retailing and EV aggregation create similar agents' interactions, as it is shown in Figure 2.

In this energy service, the agents buy their electricity from the electricity market and sell it to the end users. This is valid for the electricity to be sold for any industrial, commercial, and residential application as well as for EVs to charge their batteries. The agents also interact in the LCFS part of EMMEV. This has been visualized in Figure 3.

In this service, the agents interact in the LCFS market to trade their credits. The agents also charge the vehicle drivers less or more based on the emissions from each specific fuel sold and the credit they get for each specific fuel.

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For simplicity, it is assumed that there is a single electricity market in the model, serving two countries. By assumption, each country is divided into two regions, with different electricity prices due to line congestion between the regions.

Models such as EMMEV create an understanding in this complex, interrelated, and multidisciplinary area. This understanding serves the regulators and policy makers to guide the transportation toward low-carbon alternatives.

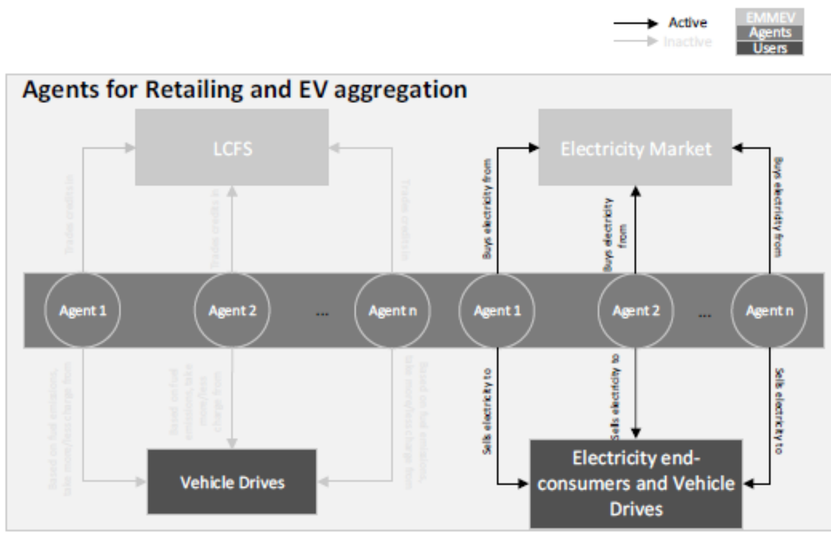


**Figure 2.** Agents interaction for retailing in electricity market.

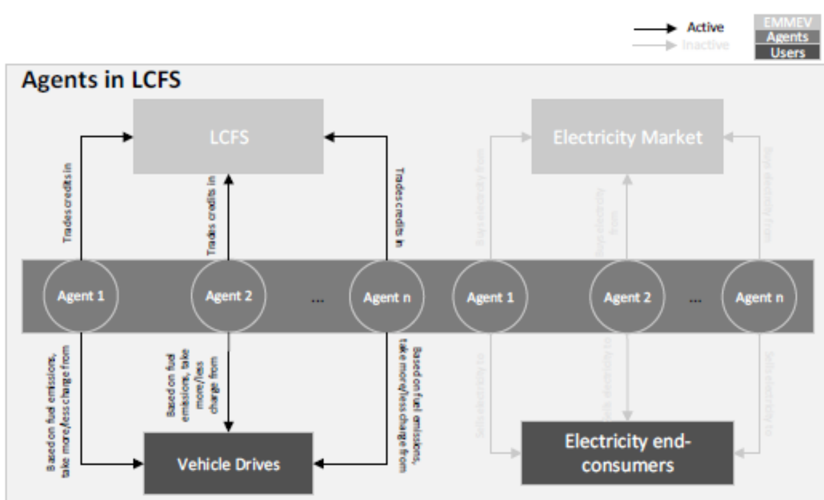


**Figure 3.** Agents interaction in LCFS.

## 4. Test System

EMMEV has been tested in a simulated market with two fictitious countries. The population of these countries are assumed to be very similar and both countries have taken serious measures for both renewable electricity generation and e-mobility. In each country, it is assumed that there are two price regions, as shown in Figure 4.

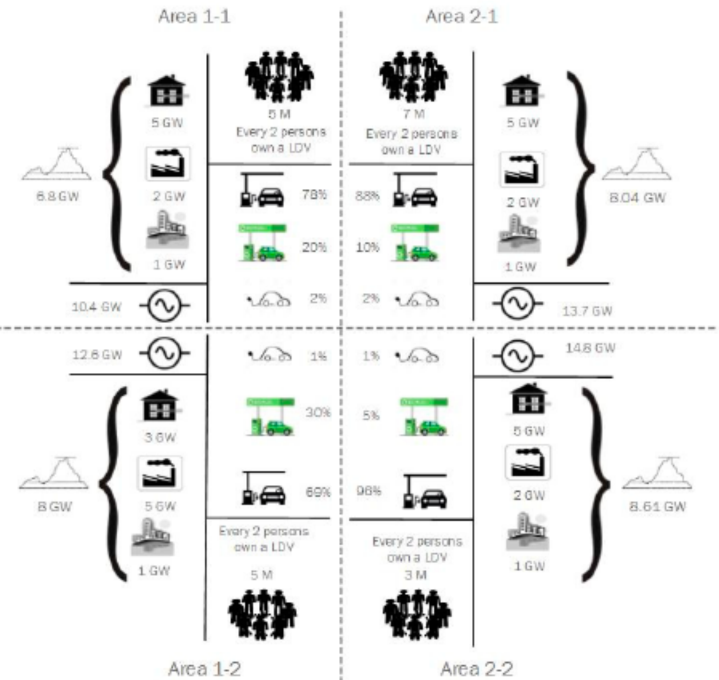


**Figure 4.** The test system structure LDV: Light Duty Vehicle.

In the figure above, four areas in the electricity market are depicted. In each area, the peak load and how the peak load is divided between residential, industrial, and commercial loads are presented. On the lower part for each area, the total generation capacity is shown. Then, the population and the number of vehicles per person are shown. Finally, the percentage share of each type of vehicle, electric, biofuel, or regular gasoline, is depicted for each area.

The parameters used in the test system are described in Table 2. The table is a summary of the parameters used for modelling purpose. It is shown whether each parameter is based on an assumption or if it is taken from other references (the reference is shown) or if the parameters are derived from other assumptions or referenced parameters.

Considering the complexity of such systems, the above-mentioned parameters are limited to our current capacity to model the system. However, there are more parameters, such as demographic information about the population (such as age, gender, and wealth), changes in electricity consumption per person and consequently in peak electricity consumption, and variation in electricity generation from each resource, which have influences on the model but are not considered for the sake of simplicity.

There are three types of loads in the market: residential, industrial, and commercial. It is assumed that all the individual loads follow the same pattern depending on their type, as shown in Figure 5.

**Table 2.** Description of the parameters in the test system.

| **About Parameters** | **General (G)** | | **Electricity Consumption (EC)** | | | **Electricity Generation (EG)** | | **Mobility (M)** | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter ID | G1 | G2 | EC1 | EC2 | EC3 | EG1 | EG2 | M1 | M2 |
| Parameter description | Number of countries in the electricity market | Population in each country | Electricity consumption per person | Peak electricity consumption | Load patterns | Power generation capacity | Share of different type of generation | Number of LDV per person | Share of each type of vehicle |
| Assumption | √ | √ | √ | - | - | √ [1] | √ | √ | - |
| Based on a reference | - | - | - | - | √ [10] | - | - | - | - |
| Derived from another parameter(s) | - | - | - | √ (G2, EC1) | - | √ (EC2, EC3) | - | - | √ (M1) |

[1] It is assumed that there is always enough extra generation. Therefore, the case of infinite electricity price is impossible to happen in this model. √: Valid point for the parameter.

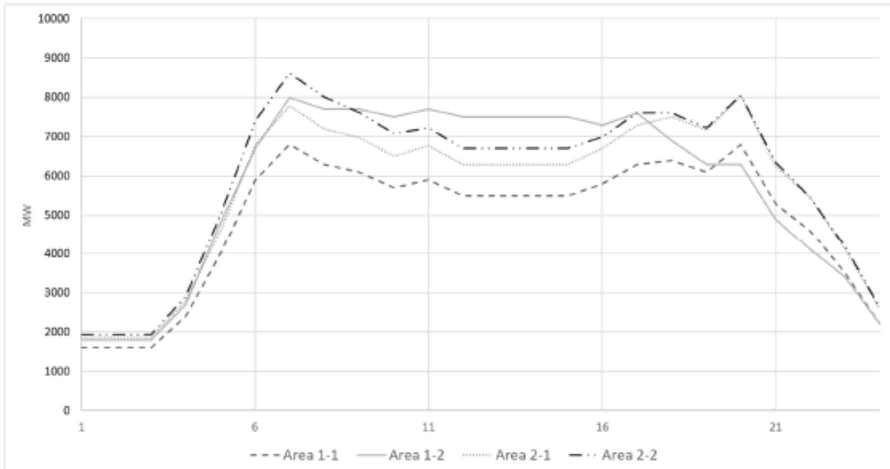


**Figure 5.** Load in 4 different areas.

In the system, there are 5 agents and their market shares are summarized in Table 3.

**Table 3.** Agents in the test system.

| Agent Number | Generation Unit (MW) | Share of Electric Vehicles Serviced by Each Agent (%) |
|---|---|---|
| 1 | 7300 | 26 |
| 2 | 17,600 | 24 |
| 3 | 8100 | 21 |
| 4 | 12,600 | 4 |
| 5 | 5900 | 26 |

The agents are ESCOs which can own generation units and provide EV aggregation services. In Figure 4, the size of the generation units owned by each agent is shown. The generation units are of different types: hydro, thermal, solar, and wind generation units. The primary share of the market from EV aggregation services is also shown in Table 3. This share can be changed by different strategies that each agent can take in the LCFS market.

The EVs in this simulation environment have a battery capacity of 8 kWh with a charging power of 3 kW/h. The battery capacity and charging power are fairly low in comparison with existing electric vehicles. However, due to lower penetration of EVs, this can be still a valid assumption [45].

There are three fuel types in the test system, which are described in Table 4.

**Table 4.** Fuel alternatives in the test system.

| Fuel Type | $gCO_2/MJ$ | EER | Primary Fuel Share |
|---|---|---|---|
| Electricity | 20 | 3.4 | 1.58 |
| Biofuel | 40 | 1 | 18.65 |
| Diesel/Gasoline | 98 | 1 | 79.77 |

The target is to decrease emissions from transportation by 10% by the end of 2030 starting from 2016. Based on this target, the number of electric vehicles which are needed to reach that target is set. LCFS is set to reach a target and EMMEV has been studied how effectively LCFS can reach that target.

The increase in the number of EVs will eventually influence the electricity price. The process which EMMEV follows to get the outputs are visualized in Figure 6.

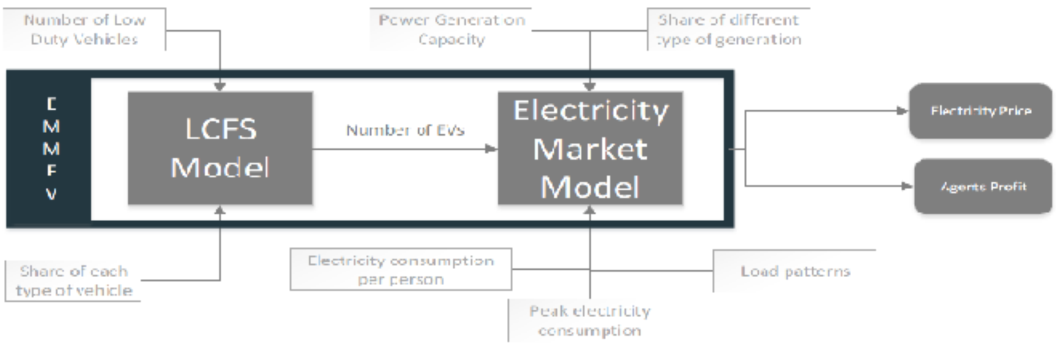


**Figure 6.** EMMEV process.

In this process, the number of EVs, the output from the LCFS model, is an input to electricity market. Therefore, the number of EVs will influence the electricity price, which is discussed and analyzed in the next section of this paper.

## 5. Results and Discussions

The agents can sell their credits in the Ongoing Credit Market or Credit Clearing Market as described in Section 2. If regulated parties do not have contracts in the ongoing LCFS Credit Market or there are overall credit shortfalls and the regulated parties reported net credit deficits at the end of the reporting period, then a Credit Clearing Market will occur. Therefore, it is assumed that all the credits are sold in the Ongoing Credit Market.

As described above, the regulators in the LCFS program set a maximum price for credits each year. This price will increase each year based on inflation and other economic parameters [34]. As shown in Figure 4, the initial percentage of EVs in each area is between 1% and 2% and the total EV penetration is 1.58%. As shown in Figure 7, the price of credits increases between 0 to 5.5% and the final penetration of EVs (in percent) is depicted.

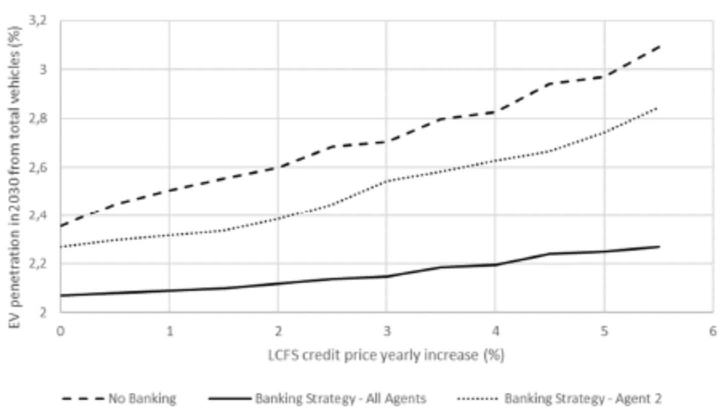


**Figure 7.** Impact of LCFS credit prices increase on EV penetration.

In the above figure, banking strategy is shown to have a negative influence on EV penetration. This is because the market is not cleared often enough to give enough liquidity of credits to increase EV penetration. The more agents bank their credits, the lower the liquidity reducing the penetration rate of EVs.

In the LCFS market, the agents mainly trade their credits in the ongoing LCFS credit market, which is a forward market with bilateral agreements. As a drawback to EMMEV and in general in LCFS, the Credit Clearance Market happens rarely, since this requires a widespread market (which is not the case in EMMEV) and if that happens more frequently, it will help the credit price competitiveness and more competition among the agents.

*Electricity Prices*

The electricity prices are determined by crossing the electricity demand curve with the electricity supply curve in each area. Electricity prices without any EVs in the system are shown in Figure 8. As it can be seen above, the electricity price in EMMEV increases linearly when the consumption increases. It is assumed that the generation units will keep their capacity during the period that EMMEV is modelled and there is always enough generation for the demand. In Figure 9, the changes in electricity prices as result of the LCFS are shown. The electricity price increases on average by 1–2% per year. In the next figure, the changes of electricity prices as result of the LCFS with agents implementing a banking strategy are shown.

The size of electricity consumption by EVs in comparison to the overall electricity consumption is very low. The electricity price increase is less than 2% in all the areas because of the implementation of the LCFS. In addition, the size of the EV fleet does not change considerably through the implementation of the LCFS.

The electricity price changes are dependent on both demand and supply. As the electricity supply function is a step function, an increase in demand can increase or keep the electricity price levelled, as can be seen in Figure 9. The banking strategy has a small negative impact on the number of EVs and, consequently, on electricity prices, as shown in Figure 10. The electricity prices changed more in the banking-strategy case than in the no-banking-strategy case. The percentage of change in electricity price between banking and no-banking strategy is very low. The low share of the total electricity consumption by EVs is the main reason. The average year-to-year change in electricity price is 0.47% in the no-banking case and 0.54% in the banking case.

The sensitivity analysis is described in Table 5.

This sensitivity analysis is performed by running the model by varying a parameter and keeping all other parameters fixed. The sensitivity results (neutral, linear proportional, high, and low) in Table 4 are shown in relative measures to make them comparable with each other. Electricity consumption per person, peak electricity consumption, and share of different types of generation units can influence the penetration of EVs in 2030. On the other hand, the number of LDV (Low Duty Vehicles) per person and share of each type of vehicle can have a large influence on electricity prices.

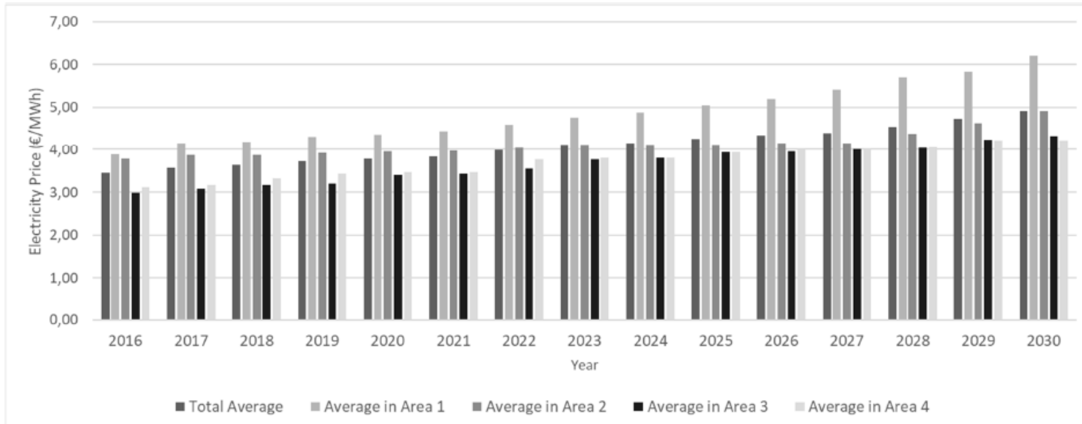


**Figure 8.** Average electricity prices in four areas and average in all areas from 2016 to 2030.

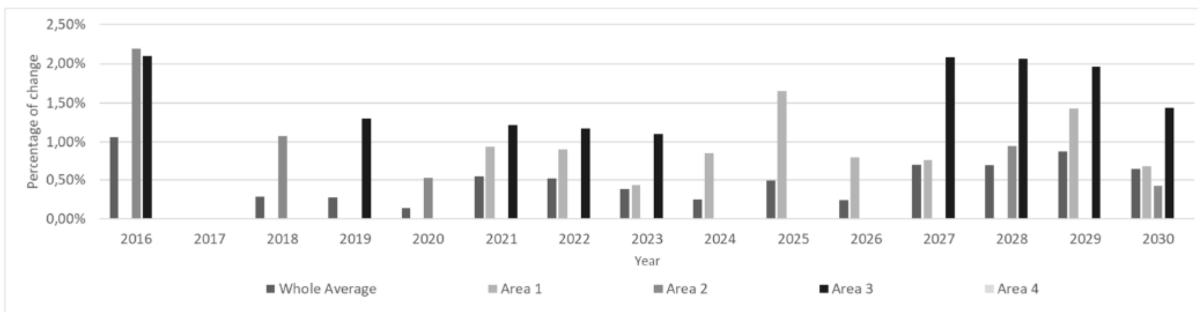


**Figure 9.** Changes of electricity prices (%) with EVs and LCFS (no banking).

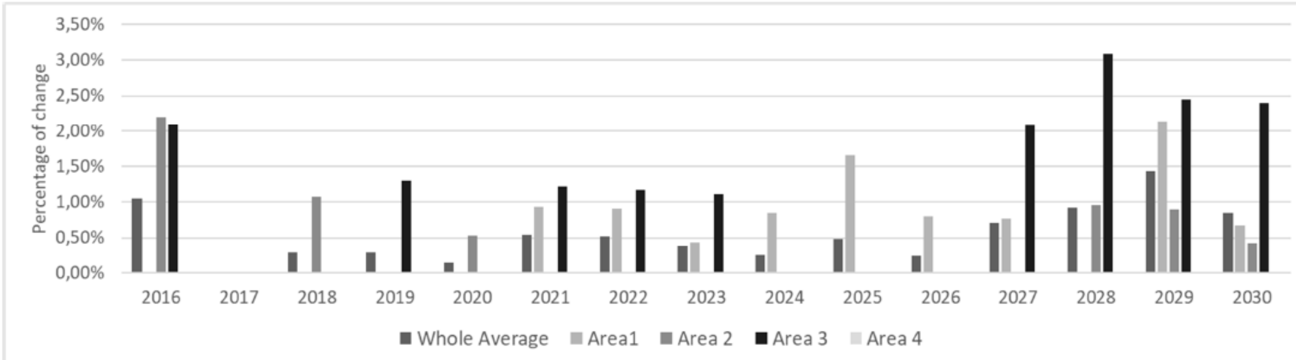


**Figure 10.** Change in electricity price (%) with EVs and LCFS (with banking).

**Table 5.** Sensitivity analysis of variables.

| Parameter | Number of Countries in the Electricity Market | Population in Each Country | Electricity Consumption per Person | Peak Electricity Consumption | Load Patterns | Power Generation Capacity | Share of Different Type of Generation | Number of LDV Per Person | Share of Each Type of Vehicle |
|---|---|---|---|---|---|---|---|---|---|
| Sensitivity of EV penetration in 2030 in relation to | Neutral | Linear proportional | Neutral | Low | Low | Low | Low | High | High |
| Sensitivity of electricity price in relation to | Neutral | Linear proportional | High | High | Depends on the pattern | High | High | Neutral | High |

## 6. Conclusions

The LCFS is a policy with the aim to promote low-carbon fuels. In this paper, an agent-based model called EMMEV is developed to investigate the influence of the LCFS on the number of EVs and on electricity price.

The effectiveness of this policy is mainly dependent on wide geographical spread, resilience of market liquidity, and price competitiveness. Based on the assumption that agents reinvest the revenue from the LCFS on EV charging infrastructure or other EV-promoting activities, such as incentives, the effect of the LCFS on the adoption of low-carbon vehicles is quite small, as demonstrated in this paper. Consequently, the impact of an increased number of EVs on electricity prices is not considerable.

In EMMEV, it is assumed that the agents only trade in the Ongoing Market, since the regulated parties have contracts in the ongoing LCFS Credit Market and there are no credit shortfalls. It is also assumed an elasticity of each additional station per 100,000 residents would increase its EV market share by 0.12% and the profits from the LCFS are spent in charging infrastructure (although other studies have shown that rebates might be more effective [46]). The results from EMMEV show that the impact of the LCFS on EV penetration is low. It is also indicated that the LCFS is not an effective driver for EV penetration in a small geographical area with low liquidity. The LCFS seems to need large regulated parties to guarantee the resiliency required for market liquidity, since supply and demand are dependent on a larger number of participants.

Market liquidity is one of the important factors for financial stability and real trade activity in the LCFS. Low market liquidity downgrades the efficiency of the market [47] but is also the result of inefficient design of the market. The regulators should follow the market changes every year to target a right level and adapt the supply and demand of credits to ensure trade activities in the market. In case of low market liquidity, the LCFS will be fragile and likely to evaporate in response to shocks. As described above, LCFS can be effective when the market is spread in wide geographical areas to ensure enough credits in the market. The credit prices will also become less unpredictable in case of higher market liquidity. Highly uncertain prices will decrease participation of fuel distributors in the market and will make it hard for investors to make long-term decisions.

The price competitiveness in the LCFS is dependent on more regular Credit Clearing Markets. Bilateral contracts will not give enough confidence to investors to be ensured that they can sell their credits and have credible predictions of the credit price. On the other hand, those agents who have not met their previous year-end obligation can use Credit Clearing Markets to provide additional compliance flexibility. The results from this paper show that the banking strategy of the agents contributing to the LCFS can have a small negative impact on penetration of EVs, unless there is regular Credit Clearance. A regular Credit Clearance can neutralize the effect of banking by providing buyers and sellers flexibility to negotiate mutually beneficial transactions.

From the electricity market perspective, the initial influence of EVs penetration on electricity prices is low. The electricity price in both the banking and no-banking case did change, but very marginally. Even in case of high EV penetration, the influence on electricity price is not considerable [10].

As with many policies, the design and context of implementation of the LCFS will have an influence on its performance. We have shown, in a simplistic model, that in a small market without credit clearance some agents might choose to bank their credits, leading to a lower EV penetration rate than what could otherwise be expected.

The interdependence of transportation policies and the electricity market is increasing due to increasing number of Electric Vehicles while these two historically had low interdependence. This paper both introduced EMMEV and also started the investigation of the impact of LCFS on the electricity market. In the future, EMMEV will be used to investigate the impact of other low-carbon policies on the electricity market.

The LCFS is an efficient policy driver to decrease carbon emissions in transportation in the long term and in wide geographical areas. This can be a good fit on the European Commission level, so each member state, apart from their local policies to decrease emissions in transportation, can contribute to a future green vision for transportation in Europe.

**Author Contributions:** A.K. conceived and designed the model, EMMEV. He has done coding of the model in Java and development of test system. J.A.P.L. contributed in the development of the conceptual model and M.A.d.R. contributed in development of the codesand definition of the agents. A.K. wrote the paper and the paper is revised and edited by Frances Sprei, associate professor at Chalmers University of Technology, J.A.P.L. and M.A.d.R.

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## References

1. United Nations Framework Convention on Climate Change. Available online: https://unfccc.int/resource/docs/convkp/conveng.pdf (accessed on 13 July 2018).
2. International Energy Agency. *Transport, Energy and $CO_2$: Moving Toward Sustainability*; Organization for Economic Co-Operation and Development: Paris, France, 2009.
3. Barker, T.; Bashmakov, I.; Bernstein, L.; Bogner, J.; Bosch, P.; Dave, R.; Davidson, O.; Fisher, B.; Grubb, M.; Gupta, S. *Climate Change 2007: Mitigation of Climate Change*; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2007.
4. International Energy Agency. *Global EV Outlook 2016—Beyond One Million Electric Cars*; Organization for Economic Co-Operation and Development: Paris, France, 2016.
5. Burleson, E. Paris Agreement and Consensus to Address Climate Challenge. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2710076 (accessed on 13 July 2018).
6. Eberle, U.; Helmolt, R.V. Sustainable transportation based on electric vehicle concepts: A brief overview. *Energy Environ. Sci.* **2010**, *3*, 689–699. [CrossRef]
7. Fazeli, R.; Leal, V.; Sousa, J.P. A multi-criteria evaluation framework for alternative light-duty vehicles technologies. *Int. J. Multicriteria Decis. Mak.* **2011**, *1*, 230–251. [CrossRef]
8. Overview of $CO_2$-Based Motor Vehicle Taxes in the EU. Available online: https://www.acea.be/publications/article/overview-of-co2-based-motor-vehicle-taxes-in-the-eu (accessed on 13 July 2018).
9. Sierzchula, W.; Bakker, S.; Maat, K.; Wee, B.V. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy* **2014**, *68*, 183–194. [CrossRef]
10. Ahmad, K. Analysis of Integration of Plug-in Hybrid Electric Vehicles in the Distribution Grid. Master's Thesis, Royal Institute of Technology, Stockholm, Sweden, 2009.
11. Lopes, J.A.P.; Soares, F.J.; Almeida, P.M.R.; Baptista, P.C.; Silva, C.M.; Farias, T.L. Quantification of technical impacts and environmental benefits of electric vehicles integration on electricity grids. Proceedings of 8th International Symposium on Advanced Electromechanical Motion Systems & Electric Drives Joint Symposium, Lille, France, 1–3 July 2009.
12. Hadley, S.W.; Tsvetkova, A.A. Potential Impacts of Plug-in Hybrid Electric Vehicles on Regional Power Generation. *Electr. J.* **2009**, *22*, 56–68. [CrossRef]
13. Yeh, S.; Sperling, D.; Griffin, M.; Khanna, M.; Leiby, P.; Msangi, S.; Rhodes, J.; Rubin, J. National Low Carbon Fuel Standard: Policy Design Recommendations. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2105897 (accessed on 13 July 2018).
14. Farrell, A.E.; Sperling, D. A Low-Carbon Fuel Standard for California, Part 1: Technical Analysis. Available online: https://www.energy.ca.gov/low_carbon_fuel_standard/UC_LCFS_study_Part_1-FINAL.pdf (accessed on 13 July 2018).
15. Barouti, M.; Hoang, V.-D.D. Electricity as a Commodity. 2011. Available online: http://www.essectransac.com/wp-content/themes/arthemia/images/2011/04/Electricity-as-a-Commodity-M.Barouti-and-D.Hoang_.pdf (accessed on 13 July 2018).

16. Stralen, J.N.P.v.; Uslu, A.; Longa, F.D.; Panoutsou, C. The role of biomass in heat, electricity, and transport markets in the EU27 under different scenarios. *Biofuels Bioprod. Biorefin.* **2013**, *7*, 147–163. [CrossRef]
17. Reimagine Consumer Engagement. Available online: https://www.bidgely.com/ (accessed on 13 July 2018).
18. Biggar, D.R.; Hesamzadeh, M.R. *The Economics of Electricity Markets*; Wiley-IEEE Press: West Sussex, UK, 2014; Available online: http://s1.nonlinear.ir/epublish/book/The_Economics_of_Electricity_Markets_1118775759.pdf (accessed on 13 July 2018).
19. Albrecht, M.; Nilsson, M.; Akerman, J. Electrification of Vehicles–Policy Drivers and Impacts in Two Scenarios. 2013. Available online: https://onlinelibrary.wiley.com/doi/abs/10.1002/9781118568040.ch1 (accessed on 13 July 2018).
20. Foxon, T.J. Technological and Institutional 'Lock-in' as a Barrier to Sustainable Innovation. 2002. Available online: https://www.imperial.ac.uk/media/imperial-college/research-centres-and-groups/icept/7294726.PDF (accessed on 13 July 2018).
21. Seto, K.C.; Davis, S.J.; Mitchell, R.B.; Stokes, E.C.; Unruh, G.; Urge-Vorsatz, D. Carbon Lock-In: Types, Causes, and Policy Implications. *Annu. Rev. Environ. Resour.* **2016**, *41*, 425–452. [CrossRef]
22. Greene, D.L.; Patterson, P.D.; Singh, M.; Li, J. Feebates, rebates and gas-guzzler taxes: A study of incentives for increased fuel economy. *Energy policy* **2005**, *33*, 757–775. [CrossRef]
23. Sprei, F.; Bauner, D. Incentives Impact on EV Markets. 2011. Available online: http://docplayer.net/30370495-Incentives-impact-on-ev-markets.html (accessed on 13 July 2018).
24. Mersky, A.C.; Sprei, F.; Samaras, C.; Qian, Z. Effectiveness of incentives on electric vehicle adoption in Norway. *Transp. Res. Part D Transp. Environ.* **2016**, *46*, 56–68. [CrossRef]
25. Lade, G.E.; Lawell, C.-Y.C.L. The design and economics of low carbon fuel standards. *Res. Transp. Econ.* **2015**, *52*, 91–99. [CrossRef]
26. Yeh, S.; Witcover, J. Status Review of California's Low Carbon Fuel Standard. 2013. Available online: http://clean-economy.org/wp-content/uploads/2014/01/LCFS-Status-Review-Jan-2014-UCD-ITS-RR-14-01R.pdf (accessed on 13 July 2018).
27. Yeh, S.; Witcover, J. Status Review of California's Low Carbon Fuel Standard. 2014. Available online: https://merritt.cdlib.org/d/ark:%252F13030%252Fm59g721x/1/producer%252F893141744.pdf (accessed on 13 July 2018).
28. Berry, T.; Jaccard, M. The renewable portfolio standard: Design considerations and an implementation survey. *Energy Policy* **2001**, *29*, 263–277. [CrossRef]
29. Fagiani, R.; Barquín, J.; Hakvoort, R. Risk-based assessment of the cost-efficiency and the effectivity of renewable energy support schemes: Certificate markets versus feed-in tariffs. *Energy Policy* **2013**, *55*, 648–661. [CrossRef]
30. Tudor, G.G. The Norway-Sweden Certificate Market in Renewable Electricity: A Model for the European Union. 2012. Available online: https://heinonline.org/HOL/LandingPage?handle=hein.journals/texjogel7&div=13&id=&page= (accessed on 13 July 2018).
31. Swedish Energy Agency. Available online: https://www.iea.org/policiesandmeasures/pams/sweden/name-21727-en.php (accessed on 13 July 2018).
32. Low Carbon Fuel Standard. Available online: https://www.arb.ca.gov/fuels/lcfs/lcfs.htm (accessed on 13 July 2018).
33. Clean Fuels Program 2017 Rulemaking. 2016. Available online: https://www.oregon.gov/deq/Rulemaking%20Docs/CFP2017meet1sum.pdf (accessed on 13 July 2018).
34. Low Carbon Fuel Standard—Final Regulation Order. 2012. Available online: https://www.arb.ca.gov/regact/2015/lcfs2015/lcfsfinalregorder.pdf (accessed on 13 July 2018).
35. Low Carbon Fuel Standard Regulatory Guidance 16-04. 2016. Available online: https://www.arb.ca.gov/fuels/lcfs/guidance/regguidance_16-04.pdf (accessed on 13 July 2018).
36. Green, R. The electricity contract market in England and Wales. *J. Ind. Econ.* **1999**, *47*, 107–124. [CrossRef]
37. Morrison, F. *The Art of Modeling Dynamic Systems: Forecasting for Chaos, Randomness and Determinism*; Dover Publications: New York, NY, USA, 2008.
38. Benth, F.E.; Benth, J.S.; Koekebakker, S. *Stochastic Modelling of Electricity and Related Markets*; World Scientific: Singapore, 2008.
39. Parsons, S.; Wooldridge, M. Game Theory and Decision Theory in Multi-Agent Systems. *Auton. Agents Multi-Agent Syst.* **2002**, *5*, 243–254. [CrossRef]

40. Ringler, P.; Keles, D.; Fichtner, W. Agent-based modelling and simulation of smart electricity grids and markets–A literature review. *Renew. Sustain. Energy Rev.* **2016**, *57*, 205–215. [CrossRef]
41. McArthur, S.D.J.; Davidson, E.M.; Catterson, V.M.; Dimeas, A.L.; Hatziargyriou, N.D.; Ponci, F.; Funabashi, T. Multi-Agent Systems for Power Engineering Applications; Part I: Concepts, Approaches, and Technical Challenges. *IEEE Trans. Power Syst.* **2007**, *22*, 1743–1752. [CrossRef]
42. Wooldridge, M. *An Introduction to MultiAgent Systems*, 2nd ed.; John Wiley & Sons: Glascow, UK, 2009.
43. Collier, N.; North, M. Repast Java Getting Started. 2012. Available online: https://repast.github.io/docs/RepastJavaGettingStarted.pdf (accessed on 13 July 2018).
44. Suguri, H. A standardization effort for agent technologies: The foundation for intelligent physical agents and its activities. In Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences, Maui, HI, USA, 5–8 January 1999.
45. Karnama, A.; Resende, F.O.; Lopes, J.A.P. Optimal Management of Battery Charging of Electric Vehicles: A New Microgrid Feature. In Proceedings of the 2011 IEEE Trondheim PowerTech, Trondheim, Norway, 19–23 June 2011.
46. Axsen, J.; Kurani, K.S. Hybrid, plug-in hybrid, or electric—What do car buyers want? *Energy Policy* **2013**, *61*, 532–543. [CrossRef]
47. Christensen, A.; Hobbs, B. A model of state and federal biofuel policy: Feasibility assessment of the California Low Carbon Fuel Standard. *Appl. Energy* **2016**, *169*, 799–812. [CrossRef]

# Publication 3

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## ENERGY X.0: Future of energy systems

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ABSTRACT

Climate change is an existential threat for human-beings and energy sector is the prime responsible. On the other hand, the technological progress has made it possible to use sustainable resource for energy generation and consume energy more intelligently. The latest has made the large industries to be willing to take control over their own energy system. EX.0 (ENERGY X.0) encapsulates the visions for a change in the energy systems considering the technological progress and the need for a revolution to save our planet.

### Why ENERGY X.0?

There has been a long debate if the climate change is real or not. Although, the scientific proofs to support the climate change are undeniable [1] but the concerns of those who denies climate change can be addressed. To have a fair judgment, the risk of such a threat must be calculated. To calculate the risk, the severity is multiplied by the likelihood. Assuming the likelihood of the climate change is very low, the risk is anyway very high due to extremely high severity. This is a global threat, and nobody is safe if this is real. Therefore, believing that the energy sector needs a revolution to save our planet, is not any far from a fact. On the other hand, the technological progress is at a tipping point where such revolution is not a cost but makes reasonable returns on the investments.

In this paper, ENERGY X.0 concept with its four pillars is introduced. A Strength, Weakness, Opportunity and Threat (SWOT) analysis is done for three main players in ENERGY X.0.

### What is ENERGY X.0?

ENERGY X.0 encapsulates the visions for such a revolution in the energy systems considering the technological progress and the need for a revolution to save our planet [2]. The target groups for such a revolution are three main groups:

1. Utilities
2. Large Energy Consumers
3. New Players

Utilities are convectional energy providers and their interest, primarily imposed by regulators in each country, is to provide reliable energy services, reduce costs and then to keep their market position and even expand their business. Large Energy Consumers are referred to large industries or group of smaller energy consumers and their interest is to keep or even increase their security of supply and decrease their costs and dependency on utilities. The New Players in the energy market are referred to opportunistic SMEs (Small and Medium Enterprises) that their interest is to serve the needs of energy consumers and bypass utilities or at least stop them from further expansion in the new business areas [3]. Energy X.0 has four pillars as shown in Fig. 1. In Table 1, a SWOT analysis of the ENERGY X.0 for the four players in the market are shown.

### Future work

The four pillars of ENERGY X.0 will be described in more details and relevant solutions will be presented in the next phases of this work. For each pillar, the existing solutions, their advancements and value


Fig. 1. ENERGY EX.0 and its four pillars.

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**Table 1**
SWOT (Strength, Weakness, Opportunity and Threat) Analysis of EX.0 for three main players.

| | Strength | Weakness | Opportunity | Threat |
|---|---|---|---|---|
| **Renewable Energy Investment** | | | | |
| Utilities | Established market position | Low organizational agility | Potential for market expansion | Loss of market share to the New Players |
| Large Energy Consumers | Asset ownership and more control | Lack of knowledge | Energy cost reduction<br>Reduction of dependency on utilities | Loss of business focus |
| New Players | Organizational agility | Need of capital and reputation | Easy market entry due to blue ocean | Changing market environment |
| **Local Energy System** | | | | |
| Utilities | Access to end consumers | Lack of innovation ecosystem | Potential for new business opportunity | Expose to competition |
| Large Energy Consumers | Asset ownership and more control | Lack of knowledge | Contribution of low-carbon society | Higher costs and immaturity of the technology |
| New Players | Organizational agility | Low access to capital and past experiences | Create an energy disruption to get a market share from utilities | Low short-term return on investment for cash-constraint players |
| **Sustainable Transportation** | | | | |
| Utilities | Established connections | Unknown market position | Potential for new business opportunity | Loss of business focus |
| Large Energy Consumers | Asset ownership | Lack of knowledge | Contribution of low-carbon society and green branding | Higher costs |
| New Players | Organizational agility | Low access to capital | High long-term potentials | Low return on investment |
| **New Energy Solutions** | | | | |
| Utilities | Access to end-consumers data | Lack of innovation ecosystem | Potential new opportunities | Expose to competition and change of regulation |
| Large Energy Consumers | Asset and data ownership and control | Lack of knowledge and experiences | Cost saving | Cyber-security threats |
| New Players | Organizational agility and innovation | No access to data | New business opportunity and blue ocean | Pave the way for big players |

creation for the above three players will be descried. The contribution of each pillars to United Nation Sustainable Development Goals (SDGs) will be evaluated and presented.

## Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

[1] J.T. Houghton, L.G. Meiro Filho, B.A. Callander, N. Harris, A. Kattenburg, K. Maskell, Climate change 1995: the science of climate change, Clim. Change (1996) 584.
[2] S. Chu, A. Majumdar, Opportunities and challenges for a sustainable energy future, Nature 488 (7411) (2012) 294.
[3] G. Boyle, Renewable energy, in: Godfrey Boyle (Ed.), Renewable Energy, Oxford University Press, 2004, p. 456. May 2004. ISBN-10: 0199261784. ISBN-13: 9780199261789, p.456.

# Publication 4

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## Organic data centers: A sustainable solution for computing facilities

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ABSTRACT

In the present perspective article we provide an overview of on-going work in the literature and possible future development of organic data centers (ODC). These are defined as the combined operation of a data center and a greenhouse, and given their compatible thermal and operation requirements, ODCs have the potential to provide an excellent solution in terms of sustainability. In particular, we identify possible positive impacts of ODCs on at least 5 of the 17 United Nations (UN) Sustainable Development Goals (SDGs), including SDGs 2 and 13 on zero hunger and climate change, respectively.

### 1. Introduction to organic data centers (ODCs)

Large-scale data/high-performance computing (HPC) centers are progressively more widely used in a number of applications, not only in the context of information technology (IT) but also in many areas within engineering. For instance, in the United States (US) data centers consume 3% of the total electricity [1]. Any efforts to increase energy efficiency in data centers by reusing this massive amount of electricity are very valuable. Data centers require substantial amount of cooling energy, since their computing power density (i.e. the power per surface) has increased significantly over the past decades and reached a level equivalent to that of nuclear reactors [2]. Data centers are cooled by cold air or water. When it comes to air cooling this can typically be done through one of the following methods: introducing direct fresh air into data centers, indirect evaporative cooling and air handling. For data centers based on liquid cooling, chilled water from a vapour compression system is employed. In all of these scenarios, hot energy either directly or indirectly is eventually released into the air. As a result, data centers potentially have considerable amount of excess heat which can be recovered. This waste heat is considered as low-grade energy, since the temperature is typically below 35 °C.

Yang et al. [3] proposed to combine cooling tower (with free cooling) with conventional cooling modes to refrigerate data centers. In particular, they performed an energetic and economic analysis on a data center located in Jinan (China), showing the potential of reaching the energy demand of the data center, while achieving energy savings. The challenges of performing such an analysis in the context of the Mediterranean climate, which exhibits extreme temperatures in the summer season, were discussed by Jabber and Izzat [4]. They essentially highlighted the importance of carefully analyzing the complete operation cycle of the data center, and stated that free-cooling technology needs to complement the regular cooling system in order to achieve a significant increase in the system energy efficiency.

Waste heat from data centers should be transported to other energy systems so that it can be used. This energy system may be a greenhouse, swimming pool, nearby buildings, district heating, etc. Waste heat from data centers has a rather low temperature for district heating and needs to be heated up to around 85 °C. For this purpose, a heat-pump system is used to raise the temperature level, which is a process requiring some extra electricity to be used. Furthermore, the waste energy for nearby buildings and swimming pools particularly in winters are not very attractive, since they have to be raised to a higher temperature in order to be really useful. Additionally, data centers are typically not located in very populated areas. In fact, greenhouses are one of the few applications where waste heat from data centers can be used directly without any further manipulation. Greenhouses and data centers can be easily combined in order to increase the overall efficiency of the system. For this purpose, warm air can be directly extracted into a greenhouse system. Excess fresh air can then be used in order to adjust the temperature and relative humidity. The simplified combined energy system for a data center and a greenhouse is schematically shown Fig. 1.

An extended view on efficient use of data centers has been to place them in cold climates, in order to use free cooling to contribute to the cooling needs of the data center. This has been for instance the conclusion by Harvey et al. [5], who systematically assessed the thermal conditions in a number of scenarios. However, Lee and Chen [6] argued that such an analysis needs to account for the extra energy due to humidification, which is a direct consequence of introducing cold-dry air into the

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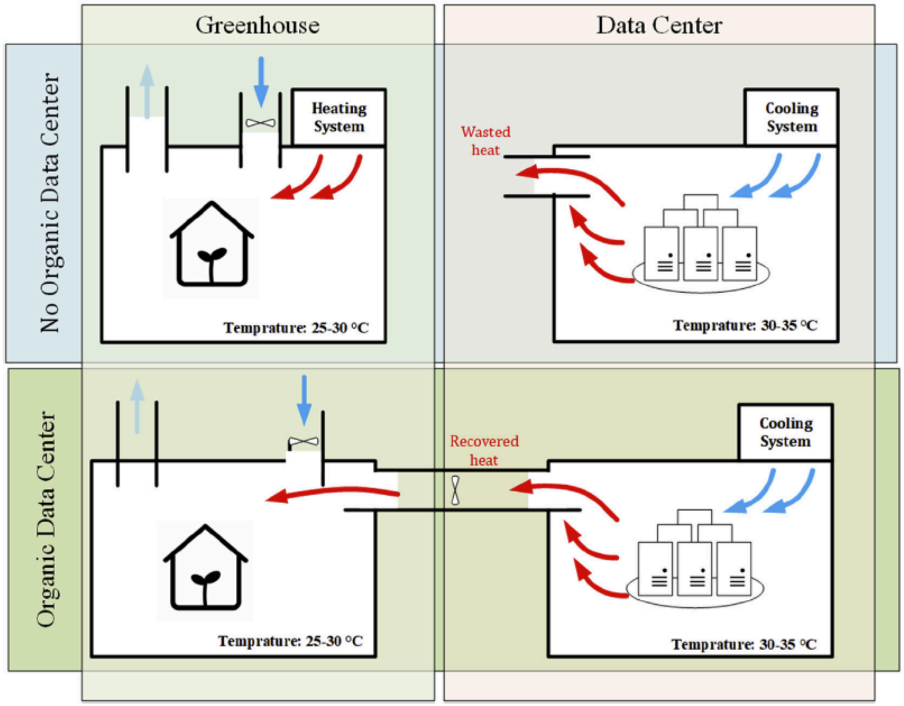



**Fig. 1.** Schematic representation of (top) a greenhouse and a data center without any heat recovery and (bottom) the coupled system with heat recovery, denoted as an organic data center (ODC). Typical temperatures from both applications are also shown.

system. By taking into account this effect, they found that the highest free-cooling potential was observed in climates exhibiting mixed-humid, warm-marine, and mixed-marine features. Oró et al. [7] provided a comprehensive view on the potential of integrating data centers into broader energy systems, with the aim of reaching more sustainable solutions, but highlighted the need of developing better metrics to actually assess the performance of such solutions. Along these lines, the review by Khalaj et al. [8] points out to operating data centers with free cooling, complemented with adequately designed hybrid energy systems and with energy storage capabilities. Furthermore, Fu et al. [9] have recently developed a comprehensive computational framework, including energetic and operation control variables, aimed at optimizing the thermal performance of data centers. These studies illustrate the high complexity of the data center operation problem, as well as the multiple ways of potential improvement.

In this study we identify that a very efficient way of using the heat produced in a data center is to couple it with a greenhouse, in order to synergistically use the produced thermal fluxes. This combination was explored by Ward et al. [10], who employed a prototype data center consisting of three racks of servers, coupled with a greenhouse, to analyze the thermal behavior of the system. They laid out the relevant thermodynamic variables of the problem and were able to model the measured data. Woodruff et al. [11] further developed this idea, framing it in the context of environmentally opportunistic computing (EOC) applications. Finally, a recent study by Sandberg et al. [12] aims at characterizing in detail the thermal performance of such coupling between data center and greenhouse, by using computational fluid dynamics (CFD) and field measurements. Note that using well-resolved flow simulations to understand the details of the flow structures and their implications for heat transfer [13,14] has a large potential when it comes to process optimization. This combination of the IT and agriculture industries is framed as the *organic data center* (ODC) concept. Note that greenhouses require cooling and heating in hot and cold seasons respectively, in addition to water, ventilation, and electricity. As shown in Fig. 1, the appropriate temperature for planting in greenhouses is within 25–30 °C, while the return air temperature in data centers is within 30–35 °C. Therefore, this relatively low-temperature heat is perfect to heat up greenhouses in cold climate conditions. The heating cost for a typical greenhouse in cold seasons can be up to one-third of the total operating costs. As a result, recovering heat from data centers considerably reduces the operating cost of greenhouses. Combining data centers and greenhouses has additional advantages. For example, the cost for ventilation is reduced as the return air from data centers has already some kinetic energy. Furthermore, due to the availability of hot free energy from the data center, it does require very high-quality insulating material within the structure (e.g. it is possible to use single glass instead of double glass). Consequently, all the running costs for greenhouses are considerably reduced by building them in combination with data centers.

## 2. Sustainability analysis of ODCs

The organic data center (ODC) concept discussed here constitutes an efficient solution to employ the heat produced in typical data centers and HPC facilities. Since it connects the growing industries of data and computing with a sector covering a very basic need, i.e. the food industry, a number of positive synergies can be identified regarding sustainability. In particular, by analyzing the United Nations (UN) Sustainable Development Goals (SDGs), described in Ref. [15], we identify positive impacts of ODCs on at least 5 of the 17 goals. Firstly, the implementation of ODCs would positively impact SDG 2 on zero hunger, due to the efficient use of the heat from the data center for more efficiently producing food. In particular, Target 2.4 (on sustainable food production systems) would benefit from the synergy in energy use from ODCs, in terms of resilience of food production but also regarding robustness towards changing climatic conditions. Clearly there is another related positive impact on SDG 7, related to affordable and clean energy, due to the fact that the heat used for the greenhouse is directly extracted from the data center as part of its operation (as discussed above), and therefore it comes at no additional cost. Additionally, HPC-enabled solutions may lead to more efficient operation of energy systems [16,17], which also support the mentioned positive impact.

ODCs would be expected to also have a positive impact on the sustainability of industry and cities, represented by SDGs 9 (on industry, innovation and infrastructure) and 11 (on sustainable cities and communities), respectively. The more efficient use of energy from data centers would contribute towards the achievement of Target 9.4, which aims at upgrading industries to more efficiently use the available resources. We expect data centers to play a progressively more prominent role in a wider range of industries, a fact that would make this particular target especially relevant. On the other hand, ODCs will probably become relevant to Target 11.b, on implementation of policies towards resource efficiency and climate change. This also applies to SDG 13 on climate change, where a resource-efficient solution such as ODCs may have a positive impact on all its targets. We believe that Target 13.1, aimed at strengthening the resilience to the problems associated to climate is probably the most relevant in the context of ODC usage and implementation. It is important to note that, despite all the potential benefits of efficiently using the heat from data centers, there is an underlying potential negative impact on SDG 1 (on ending poverty): as argued by Vinuesa et al. [18], if the future industry will heavily rely on data centers and HPC, and most likely these resources will not be uniformly distributed worldwide, this would lead to a net increase of inequalities and therefore hinder the achievement of the UN Agenda. In any case, we believe that ODCs constitute an excellent solution in terms of efficient energy use, given the fact that the current industrial requirements point towards a wider use of HPC resources.

## 3. Concluding remarks

The number of data centers has increased drastically all over the world over the past years. Data centers are cost-driven systems which consume large amounts of power, and therefore any effort to optimize data centers towards more energy-efficient solutions will be appreciated by their operators and is considered as very positive environmental action. Cooling is a vital part of any data centers since the electronic equipment needs to be maintained within a certain temperature range. As a result, data centers produce large amounts of excess heat that can be recovered. It is thus beneficial to identify another system to be coupled with data centers. Such a system should need heat with a similar temperature requirement, and it would need to be close to data centers in order to reduce energy waste. We identify that greenhouses fulfill these requirements, and in addition to their great technical adaptability, there is an excellent synergy between the two systems. This combination of two very relevant industries, i.e. IT and agriculture, is called *organic data center* (ODC). Organic data centers may positively impact urban areas from a sustainability perspective, and they may also have a positive effect on job creation. Future extensions of the present perspective article will be aimed at performing a complete simulation of a typical ODC system, in order to characterize its performance.

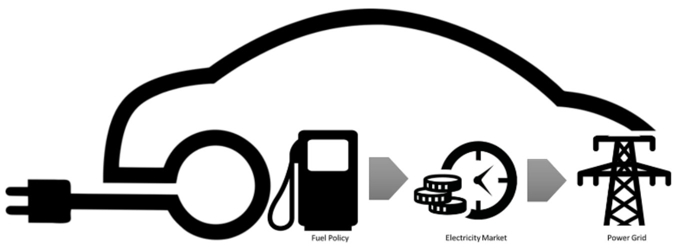
## Declaration of interests

The authors declare no conflict of interest.

## References

[1] R. Danilak, Why energy is a big and rapidly growing problem for data centers, Forbes (2017). Available at: https://www.forbes.com/sites/forbestechcouncil/2017/12/15/why-energy-is-a-big-and-rapidly-growing-problem-for-data-centers/#2c1654845a30.
[2] G. Taylor, Energy efficient circuit design and the future of power delivery", in: Proc. 18th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS) October 19-21, 2009. Portland, Oregon (USA).
[3] Y. Yang, B. Wang, Q. Zhou, Air conditioning system design using free cooling Technology and running mode of a data center in Jinan, Procedia Engineering 205 (2017) 3545–3549.
[4] S.J. Jaber, A.W. Izzat, Energy saving analysis of free cooling system in Mediterranian building, in: Proc. 10th International Conference on Advances in Science, Engineering and Technology (ICASET-18) June 20-21, 2018. Paris (France).
[5] T. Harvey, M. Patterson, J. Bean, Updated Air-Side Free Cooling Maps: the Impact of ASHRAE 2011 Allowable Ranges, The Green Grid (2012).
[6] K.-P. Lee, H.-L. Chen, Analysis of energy saving potential of air-side free cooling for data centers in worldwide climate zones, Energy Build. 64 (2013) 103–112.
[7] E. Oró, V. Depoorter, A. Garcia, J. Salom, Energy efficiency and renewable energy integration in data centres. Strategies and modelling review, Renew. Sustain. Energy Rev. 42 (2015) 429–445.
[8] A.H. Khalaj, K. Abdulla, S.K. Halgamuge, Towards the stand-alone operation of data centers with free cooling and optimally sized hybrid renewable power generation and energy storage, Renew. Sustain. Energy Rev. 93 (2018) 451–472.
[9] Y. Fu, W. Zuo, M. Wetter, J.W. VanGilder, X. Han, D. Plamondon, Equation-based object-oriented modeling and simulation for data center cooling: a case study". Energy Build. 186 (2019) 108–125.
[10] E.M. Ward, M.L. Goedke, P. Brenner, D.B. Go, A simplified thermodynamic model for waste heat utilization from a containerized data center experimental platform, in: Proc. 13th InterSociety Conference on Thermal and Thermomechanical Phenomena in Electronic Systems, 2012, pp. 521–529. San Diego, CA.
[11] J.Z. Woodruff, P. Brenner, A.P. Buccellato, D.B. Go, Environmentally opportunistic computing: a distributed waste heat reutilization approach to energy-efficient buildings and data centers, Energy Build. 69 (2014) 41–50.
[12] M. Sandberg, M. Risberg, A.-L. Ljung, D. Varagnolo, S. Xiong, M. Nilsson, A modelling methodology for assessing use of datacenter waste heat in greenhouses, in: Proc. 3rd International Conference on Environmental Science and Technology, October 2017, pp. 19–23. Budapest (Hungary).
[13] H.M. Nagib, A. Vidal, R. Vinuesa, Vorticity fluxes: a tool for three-dimensional and secondary flows in turbulent shear flows, J. Fluids Struct. 89 (2019) 39–48.
[14] A. Vidal, H.M. Nagib, R. Vinuesa, Vorticity fluxes and secondary flow: Relevance for turbulence modeling, Phys. Rev. Fluids 3 (7) (2018) 72602.
[15] UN General Assembly (UNGA), Transforming our world: the 2030 agenda for sustainable development, Resolut (2015) 25 1–35. A/RES/70/1.
[16] H. Cachafeiro, L.F. De Arevalo, R. Vinuesa, J.J.B. Goikoetxea, Impact of solar selective coating ageing on energy cost, Energy Proc. 69 (2015) 299–309.
[17] R. Vinuesa, L.F. de Arévalo, M.H.C. Luna, Simulations and experiments of heat loss from a parabolic trough absorber tube over a range of pressures and gas compositions in the vacuum chamber, J. Renew. Sustain. Energy 8 (2) (2016), 023701.
[18] R. Vinuesa, H. Azizpour, I. Leite, M. Balaam, V. Dignum, S. Domisch, A. Felländer, S. Langhans, M. Tegmark, F. Fuso Nerini, The Role of Artificial Intelligence in Achieving the Sustainable Development Goals", 2019 arXiv:1905.00501.

# Electrification of Transportation: From Fuel Policy to Electricity Market and EV Battery Charging in Microgrids



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