Deliverable 9.2

Smart (and less smart) large-scale integration of EV into European power systems

Final report

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List of Abbreviations

AC/DC	Alternating/Direct Current
ACEA	Association des Constructeurs Européens d'Automobiles (European Automobile Manufacturers Association)
ASHP	Air-Source Heat Pumps
BaU	Business as Usual
CAPEX	Capital Expenditure
CCGT	Combined-Cycle Gas Turbine
CCS	Carbon Capture and Storage
CHP	Combined Heat and Power
CO_2	Carbon dioxide
COP	Coefficient of Performance
CSP	Concentrated Solar Power
DE-DK	Germany and Denmark (electricity systems)
DR	Demo Region
DSIM	Dynamic System Investment Model
DSR	Demand-Side Response
DT	Distribution Transformer
DW	Dishwashers
ECF	European Climate Foundation
EHV	Extra High Voltage
EU	European Union
EV	Electric Vehicle
FD	Fractal Dimension
FP7	Seventh Framework Programme
FR	Frequency Regulation
G4V	Grid-for-Vehicles
GB	Great Britain
GeM	Green eMotion
GHG	Greenhouse Gas
GMT	Ground-Mounted Transformer
HV	High Voltage
HVAC	Heating, Ventilation and Air Conditioning
LCA	Life-Cycle Assessment
LOLE	Loss of Load Expectation

LOLP	Loss of Load Probability
LV	Low Voltage
MERGE	Mobile Energy Resources in Grids of Electricity
MSG	Minimum Stable Generation
MV	Medium Voltage
NTS	National Transport Survey
OCGT	Open-Cycle Gas Turbine
OPEX	Operating Expenditure
PMT	Pole-Mounted Transformer
PV	Photovoltaic
R&D	Research and Development
RES	Renewable Energy Sources
TD	Tumble Dryer
UK-RI	United Kingdom and Republic of Ireland (electricity systems)
V2G	Vehicle-to-Grid
WACC	Weighted-Average Cost of Capital
WM	Washing Machine
WP	Work Package

Executive Summary

This report represents the Deliverable 9.2 of Green eMotion (GeM) project, with the key objective of developing and applying a novel whole-system analytical framework to understand the simultaneous impact of electricity demand for electric vehicle (EV) charging on the operation of electricity system as well as the required investment into generation, transmission and distribution infrastructure. This analysis estimates the economic and environmental impact of a Europe-wide EV rollout on the operation and design of European electricity system considering the 2030 horizon.

The scenario used for calculations is based on the 2030 European system characterised by high share of renewable sources, which contribute to electricity supply with about 60%.[1] Sizes of European passenger vehicle fleets are estimated based on actual European car density data, while the analysed levels of EV penetration in 2030 were 5% (Low), 15% (Medium) and 30% (High). This covers a broad range of projected EV penetrations, where 30% can be considered as an extremely high penetration from today's perspective. Individual systems studied for the impact of EV deployment included: 1) Spain, 2) Italy, 3) Germany and Denmark and 4) UK and Ireland.

The impact of EV rollout is assessed using advanced whole-electricity system modelling framework capable of assessing the impact of EVs on different segments of the electricity system, simultaneously considering distribution network, transmission network and generation system, across the range of time horizons from real-time system balancing to investment time scale.

Key findings of the analysis in this report are as follows:

- The incremental cost of supplying EV demand is a function of EV charging control strategies. In the uncontrolled case (i.e. with no smart EV demand shifting or ancillary service provision), the incremental annualised cost of electricity supply per EV is around €200/EV/year for EV penetration levels between 5% and 30%, and is relatively robust across all four analysed systems (within ±10% around €200/EV/year, increases slightly at higher penetrations). As illustrated in Figure E.1, the dominant component of additional cost is the OPEX increase, followed by increases in distribution and generation CAPEX driven by disproportionately high increase in peak demand, and only slight changes in additional transmission CAPEX.

- If there is an opportunity to control the shifting of EV demand without compromising the users' ability to make their journeys, this smart scheduling significantly reduces the incremental cost to supply EV demand. As shown in Figure E.1, the highest incremental cost levels with smart scheduling are observed in the German-Danish system (between €113 and €146/EV/year), while in the other three systems this was between €55 and €110/EV/year across the analysed cases (higher values generally correspond to higher EV penetrations). The largest contribution to cost reduction is

[1] High RES penetration assumed in our studies is in line with the long-term EU carbon emission targets. Our previous work suggests that the benefits of smart EV charging would reduce by broadly 50% in systems with low RES penetrations, mostly due to the decrease in OPEX savings.

through OPEX savings (i.e. improved generation efficiency), followed by distribution and then generation CAPEX savings.

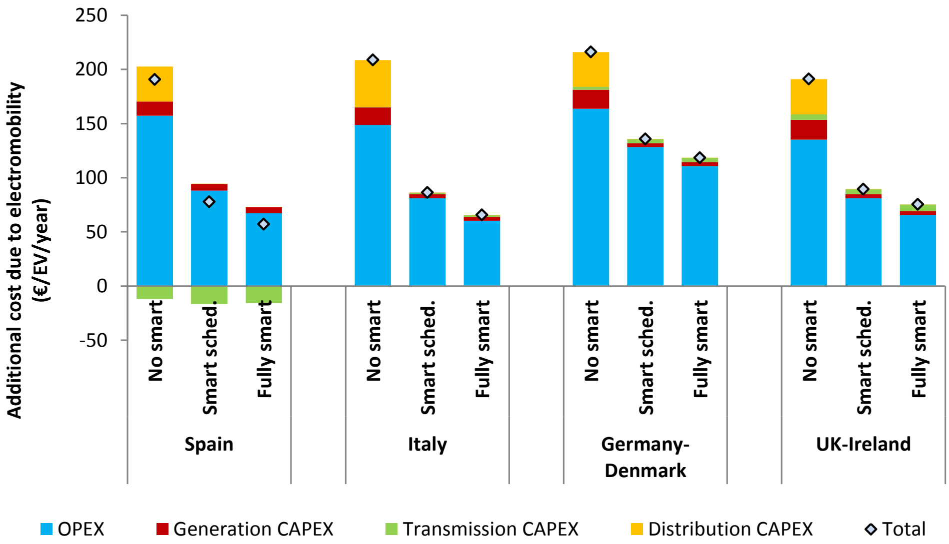

Figure E.1 Additional cost of supplying EV demand in 2030 across four systems (Medium EV penetration)

- The value of EVs providing frequency regulation (FR) is also found to be considerable. The combined participation in smart EV scheduling and FR provision reduces the cost further to between €97 and €134/EV/year in the case of Germany and Denmark, and €32-94/EV/year for the other three systems (higher values again correspond to higher EV penetrations). Figure E.1 shows that the cost savings generated by FR provision are almost exclusively made up of OPEX savings from displacing part-loaded conventional generation as FR providers.

- The analysis of CO_2 emissions from electricity systems shows that smart EV demand scheduling and FR provision can also result in greatly reduced carbon emissions from electricity sector, the magnitude of which depends on the system properties. Carbon footprint of supplying electricity to EVs with no smart EV control varies between 320 $kgCO_2$ in the UK-Ireland system (equivalent to 26 gCO_2/km for an average annual distance travelled) and 415-497 $kgCO_2$/EV/year (34-40 gCO_2/km) in the other three systems. Implementing the fully smart EV control (both scheduling and FR provision) reduces the carbon emissions to about 90 to 340 $kgCO_2$/EV/year (about 7-21 gCO_2/km) in all systems except the UK-Irish one, where we observe the drop in incremental emissions to the level of –40 to 25 $kgCO_2$/EV/year (about –3 to 2 gCO_2/km) i.e. the carbon emissions from the electricity system may even decrease as the result of integrating smart EVs (before any emission offsets in road transport are considered). Emissions in both smart and non-smart cases are significantly lower than tailpipe CO_2 emissions associated with ICE vehicles in the EU (127 g/km for new vehicles in 2013, with the target to reduce this to 95 g/km by 2021). We further find that smart EV management approaches also have the potential to deliver considerable reductions in curtailment of intermittent renewable output such as solar and wind. Figure E.2 presents the carbon emissions associated with supplying EV demand (left), as well as the impact of EV deployment on the expected level of curtailed renewable output (right).

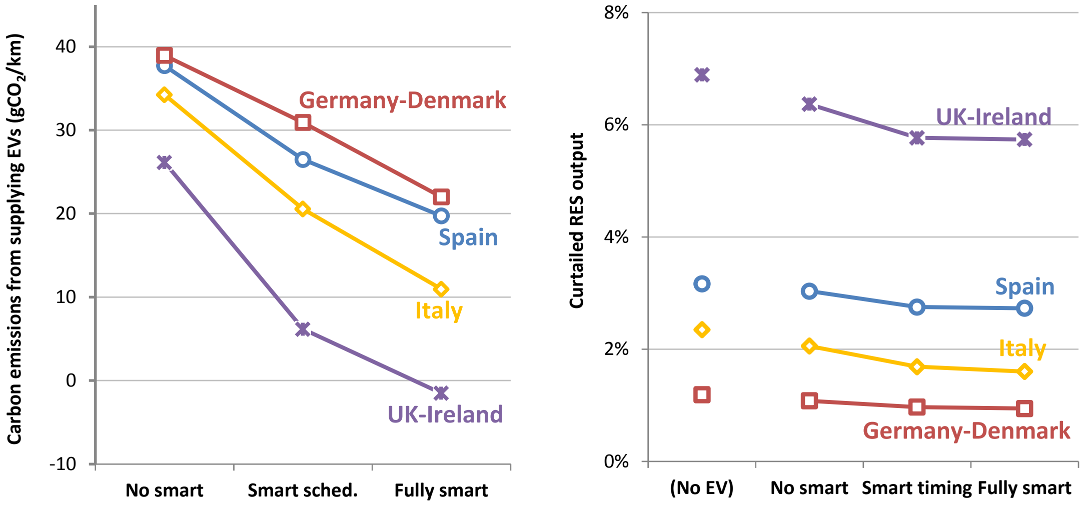

Figure E.2 Carbon emissions driven by supplying EV demand (left) and renewable output curtailment (right) across four systems (Medium EV penetration)

The results presented in the report suggest there are significant economic opportunities for flexible EV charging that can substantially reduce the system integration cost of EV deployment, as well as mitigate the environmental impact in terms of additional carbon emissions from the electricity sector. In other words, smart integration of EVs into electricity system operation and design will not undermine their rollout, as the additional cost involved is estimated to be relatively modest.

It has to be noted that the cost savings quantified here represent the fundamental economic value of flexible EV management from a cost-optimal perspective. Our analysis does not discuss whether and to which extent this economic value would materialise in current or future market and regulatory environments or what the resulting cash flows for different players in the system would be (this is addressed in more detail in GeM Deliverable 9.4). Unlike retail electricity prices, which include components such as taxes, incentives, profit margins etc., the incremental cost figures presented in this report refer to incurred additional cost due to increased expenditure associated with the investment into and operation of electricity system infrastructure driven by electromobility. The implications of retail electricity prices on the economics of EVs are addressed in a separate GeM report (Deliverable 9.6).

We show that the *split benefits* of flexible EV demand can span multiple sectors of the electricity system – balancing and energy arbitrage, ancillary service provision, generation capacity adequacy, and transmission and distribution networks. Given that these sectors are characterised by different market structures, competition levels and regulation, it will become necessary to develop an appropriate market and regulatory framework to support a cost-efficient integration of electromobility. One of the key challenges in that respect will be to devise commercial structures that deliver adequate revenues to flexible EV owners from diverse sources of value. Creating adequate commercial arrangements for flexible EV providers is addressed in later GeM Deliverables 9.6 and 9.7.[2]

[2] Both of these reports are expected to be available from the Green eMotion website in early 2015: http://www.greenemotion-project.eu/dissemination/deliverables-evaluations-demonstrations.php.

1 Introduction

1.1 Objective and scope

This report represents the Deliverable 9.2 of Green eMotion (GeM) project, and has been prepared by Imperial College London. Its key objective is to develop a new whole-system analytical framework to understand the simultaneous impact of electricity demand for electric vehicle (EV) charging on the operation of electricity system as well as the required investment into generation, transmission and distribution infrastructure.

According to the Description of Work in Annex I of GeM Grant Agreement, Deliverable 9.2 is expected to "describe the approaches and models specifically developed in Task 9.2 to assess the economic impact of EV on the operation of power systems with different energy generation mixes and levels of flexibility, including future envisaged scenarios with plenty of carbon capture and storage (CCS) plants and intermittent resources". The results of the analysis presented in Deliverable 9.2 should "quantify and suggest how smart management of EV for ancillary services provision, made possible by the inherent storage available in the EV batteries, can facilitate the integration of intermittent renewables in the presence of inflexible conventional plants while also being beneficial in terms of power system operation cost". As a key outcome, this Deliverable will provide an "estimate of the system-wide economic impact of an EU-wide rollout of electric vehicles under different conditions". This information will be of particular relevance to policy makers concerned with developing policies and measures aimed at promoting the deployment of EVs, and will indicate the value of smart EV charging in the context of an efficient integration of electrified road transport in the future European electricity system.

In line with the fundamental objective of this work, all calculations presented in the report refer to incurred additional cost due to increased expenditure associated with the investment into and operation of electricity system infrastructure driven by electromobility. In that context, the incremental cost figures (expressed per EV) that are discussed in the report are not directly equivalent to electricity prices, which generally include a number of cost components not considered here such as taxes, renewable incentives, regulatory charges, supplier profits, retail margins etc. The implications of retail electricity prices on the economics of EVs are addressed in a separate GeM report (Deliverable 9.6). The key question addressed here is the difference in electricity system investment and operation cost for smart and non-smart EV charging approaches.

The authors would like to acknowledge the valuable support received from Jan Rasmussen from the Danish Energy Association and Dr. Heike Barlag from Siemens, whose feedback greatly helped to improve the final version of this report.

1.2 Relevance for Green eMotion

The overall aim of WP9, being the only R&D Work Package of GeM, is to assess the viability of a mass rollout of EVs across the EU, by studying their system-wide impact on the European electricity infrastructure from a multi-criteria perspective involving technical, economic, environmental and social aspects. Unlike the demonstration activities in GeM, which are linked to specific EV fleets across the GeM Demo Regions (DRs), the analysis performed in WP9 will estimate the impact of a Europe-wide EV rollout, i.e. essentially scale up the number of vehicles considered from tens to hundreds of EVs monitored in various DRs, to potentially millions of vehicles that could exist in Europe in the 2030 horizon.

In that context, the economic impact analysis of EV deployment that is the subject of this report will provide an insight into the long-term implications of a rapid increase in EV penetration from the socio-economic perspective. The quantitative evidence thus provided will help inform the policy making process by identifying the economic barriers and opportunities for a more efficient integration of electromobility in the context of accelerated decarbonisation of the European electricity sector. In particular, the issue of *split benefits*, where the cost savings from controlled EV charging may materialise in various segments of the electricity system (operation, generation, transmission or distribution), will inform the commercial and regulatory framework development by stressing the importance of commercial arrangements that are capable of adequately rewarding flexible EV owners for the value they provide across the system.

1.3 Electromobility in the context of electricity system decarbonisation

Electric vehicles are increasingly becoming one of the key policy options to enable decarbonisation of transport energy demand, shifting it from fossil fuel towards electricity which could potentially be obtained from renewable and other low-carbon technologies. Nevertheless, a number of technological, economic and regulatory barriers still need to be overcome in order to facilitate a widespread adoption of EVs.

European Union has adopted ambitious targets in terms of mitigating climate change through reducing emissions of greenhouse gases (GHGs). In October 2009, the European Council set an economy-wide GHG abatement objective of 80-95% below 1990 levels by 2050. The study “Roadmap 2050: a practical guide to a prosperous, low carbon Europe”, initiated by the European Climate Foundation (ECF), derived the implications of this target for European industry and in particular for the power sector, showing that the transition to a fully reliable, fully decarbonised power sector by 2050 is a pre-condition for achieving the 80% economy-wide emissions reduction target [1].

This was confirmed by the European Commission in March 2011 through its publication of “A roadmap for moving to a competitive low carbon economy in 2050” [2]. In that document, the Commission set out sectoral carbon dioxide reduction trajectories with a mid-term view on 2030 to steer the decarbonisation of the economy on a manageable and cost-effective course. For the power sector, the Commission proposed a CO_2 reduction range of between 54% and 68% by 2030 compared to 1990 levels.

One of the key concerns for future low-carbon electricity systems is that they may be characterised by much lower generation and network asset utilisations given the significant penetration of low capacity value wind generation combined with a potential increase in peak demand that is disproportionately higher than the increase in energy, which may be driven by shifting some of the transport sector demand into electricity.[3] However, the transport sector based on EVs would be characterised by significant inherent storage capability, and this opens up opportunities for utilising more efficient charging strategies, not only to optimise electricity production capacity, but also to enhance the efficient usage of network capacity. Furthermore, smart EV charging also offers the potential for cost-efficient provision of flexible frequency regulation services, the requirements for which are assumed to increase significantly in electricity systems based on low-carbon generation technologies.

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[3] Similar trends are forecasted for the electrification of heating sector, relying on electric heat pumps rather than fossil fuel-fired boilers.

Delivering the carbon reduction targets cost-effectively through appropriate EV charging will require a fundamental shift from a passive to an active philosophy of network control. This shift, enabled by the incorporation of demand management into system operation and design, can be facilitated by the application of an appropriate information, communication and control infrastructure, which has been the subject of study of other GeM project deliverables (such as D3.2 and D3.9[4]).

Based on typical vehicle usage patterns and specific features of the EV technology, EV loads appear to be particularly well placed to support system operation, for the following reasons:

- The additional energy requirements for EV charging is relatively modest compared to the original electricity demand.

- Driving times generally associated with the majority of small passenger vehicles are relatively short, with most vehicles being stationary for over 90% of time during a typical day.

- Given that EV batteries have relatively high power ratings and significant amount of inherent storage when considered in aggregation, they could potentially be used as flexible demand resource to enable more efficient system operation.

There is clearly considerable flexibility regarding the time when the vehicles can be charged and this can provide significant benefits both to the operation and design of distribution and transmission networks as well as to the efficient dispatch and utilisation of generation capacity. This flexibility can be further enhanced through *vehicle-to-grid* (V2G) applications that involve discharging car batteries (exploiting the energy stored in the battery) to support the grid. EVs could also make a contribution to the provision of fast frequency regulation services through rapid disconnection while charging or injecting power from car batteries.

1.4 Previous assessments of system impact of EVs

Two recent FP7 projects have addressed the issue of evaluating the system impact of EVs:

- **Grid for Vehicles (G4V):** Analysis of the impact and possibilities of a mass introduction of electric and plug-in hybrid vehicles on the electricity networks in Europe[5]

- **Mobile Energy Resources in Grids of Electricity (MERGE):** Preparing Europe's Grid for Electric Vehicles[6]

Deliverable 3.1 of the G4V project [3] studied the economic and environmental impacts of large-scale introduction of EVs into the electricity systems of the UK, Spain and Sweden in the 2030 horizon. The report studied the potential contribution of smart EV charging to reducing the system operation cost and generation adequacy requirements (the possibility to deliver benefits in both areas simultaneously was not explicitly considered). Environmental

[4] Both of these deliverables are available from the Green eMotion website: http://www.greenemotion-project.eu/dissemination/deliverables-ict-solutions.php.
[5] http://www.g4v.eu/.
[6] http://www.ev-merge.eu/.

performance has been assessed in terms of mitigated greenhouse gas emissions and avoided wind curtailment as a consequence of introducing flexible EV demand into the system. The impact of EV demand on reinforcements in distribution networks was considered in another WP, but only for specific example networks without the attempt to generalise findings on the level of entire countries or regions.

An example of annual operating cost evaluations for the GB system in G4V D3.1 is provided in Figure 1.1. The cost clearly increases with higher EV penetrations, but the level of increase is highly dependent on the charging strategies adopted. Cases with controlled charging (OptUni) and with controlled charging and discharging (OptV2G) result in a visibly lower incremental cost, implying a more cost-efficient integration of electrified transport.

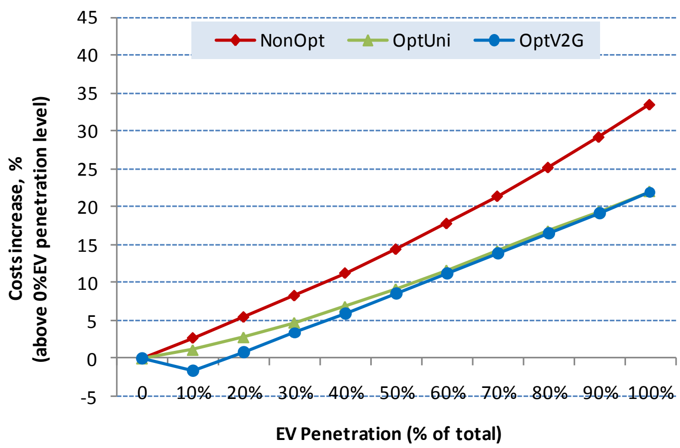


Figure 1.1 Incremental annual operating costs in 2030 GB system for varying EV penetrations and charging strategies (Source: G4V Deliverable 3.1)

In terms of the environmental impact, Figure 1.2 illustrates the results of the same study with respect to annual carbon emissions and percentage of curtailed wind output in the GB system.[7] The figure shows that controlled EV charging can significantly slow the increase of (or even reduce) carbon emissions resulting from a growing number of EVs. This is particularly visible at EV uptake levels of up to 40%, where the additional EV demand causes negative or zero additional emissions in case of controlled charging. Similarly, the level of wind output that needs to be curtailed in order to balance the system drops significantly if controlled charging strategies are adopted rather than user-led charging.

[7] GB system in 2030 is assumed to include a high level of wind capacity, and is also an island system with limited interconnection capacity. The effects depicted in the figures can therefore be expected to be more pronounced than in other systems.

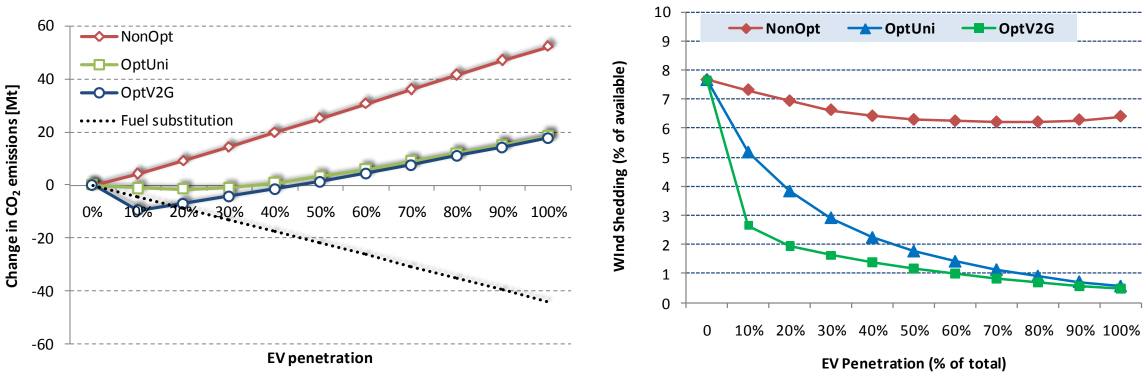


Figure 1.2 Incremental annual carbon emissions (left) and percentage of curtailed wind output (right) in 2030 GB system (Source: G4V Deliverable 3.1)

MERGE project developed a management and control concept to facilitate the actual transition from conventional to electric vehicles from the power system perspective. It also introduced enhancements of a number of existing tools used for modelling, analysing, and optimising electric networks, in order to facilitate the integration of EVs and their charging infrastructures.

The focus of the analysis in MERGE was mostly on year 2020, covering both technical aspects (distribution network performance, voltage and frequency control, reserve provision) and economic and environmental considerations (operating cost, carbon emissions and renewable integration). The developed EV control concepts identified clear benefits of smart EV charging for ancillary services provision, distribution network management and energy arbitrage (including RES integration). Deliverable 3.2 of MERGE provided an assessment of economic and environmental implications of EV deployment on generation dispatch in selected European countries. Smart charging was found to be capable of avoiding and postponing significant reinforcement of generation and distribution infrastructures.

A widely cited paper by Lund and Kempton [4] investigated the impact of various EV charging control approaches (including V2G) on the hour-to-hour performance of an energy system similar to Denmark (characterised by large shares of wind and CHP capacity). The analysis showed that EVs with night charging, and more so with increasing intelligence including V2G, will improve the efficiency of the electric power system, reduce carbon emissions and improve the ability to integrate wind power (i.e. avoid the curtailment of excess wind output).

A related paper by Kiviluoma and Meibom [5] estimated the cost of integrating EVs in the future power system of Finland for both dumb and smart charging and discharging strategies. The authors used a generation planning model and a separate dispatch model, to optimise system investment and operation including the optimisation of smart EV charging. Most of the benefits of smart EVs come from adaptive timing of charging although benefits are also accrued from provision of ancillary services and lower power plant portfolio cost. The benefits of smart EV charging in the observed system were estimated at €227/EV/year. Similar to findings of G4V studies, the introduction of EV demand under the smart charging paradigm was found to potentially reduce carbon emissions from the electricity system despite the additional energy requirements of EVs. As in [4], the benefits of smart EV charging for avoiding reinforcements of grid infrastructure were not considered in the analysis.

In summary, previous approaches studied the impact of large-scale EV deployment on various aspects of power system operation and planning (generation dispatch, network planning, generation capacity adequacy, ancillary services provision etc.). Nevertheless, there appears to be a need to integrate those aspects into a single assessment framework In order to evaluate the simultaneous impact of both uncontrolled and smart EV charging approaches on the operation and investment cost of all segments within the electricity system. This objective is pursued in the analytical work described in this report.

1.5 Report structure

The report is organised as follows. An overview of methodology, scenarios and assumptions used in the analysis is provided in Section 2. In Section 3 we provide the results of our comprehensive economic and environmental assessment of electricity system performance in the context of mass EV rollout in different European countries. Section 4 summarises the key conclusions of the report and discusses its relevance for other GeM activities and deliverables. Appendix 1 provides a description of the whole-system assessment methodology applied in this report, while Appendix 2 presents the approach to quantifying distribution network reinforcement cost driven by EV deployment.

2 Methodology, scenarios and assumptions for performing the impact assessment of EVs

This chapter discusses the whole-system assessment methodology and scenarios used to estimate the impact of widespread EV deployment in European electricity systems in the 2030 horizon. Key assumptions in these power system evolution scenarios include the generation capacity mix across different countries, demand growth, cost of network and generation capacity, and the fuel and carbon price.

2.1 Whole-system methodology for assessing the impact of electromobility on electricity systems

For the purpose of the analysis presented in this report we have developed a novel whole-systems approach to quantifying the simultaneous impact of EVs on both system operation and necessary investment in new infrastructure capacity, including generation, transmission and distribution. This assessment is performed within a single analytical framework capable of simultaneously considering the impact of EVs on different segments of the electricity system. A detailed description of the methodology is given in Appendix 1.

The impact of a high uptake of EVs in a system is analysed within a single analytical framework, which can reveal trade-offs between objectives in various sectors pursued by controlled EV charging strategies, for different future development scenarios, both on EV and energy system side. This approach has the potential to close the gap in analysing the system impact of EVs and inform the EU policy makers, regulators and the wider industry about the appropriate commercial and regulatory arrangements to facilitate a cost-effective integration of EVs in the existing and future electricity infrastructure.

In order to evaluate the whole-systems impact of massive rollout of EVs in future low-carbon electricity systems, a new analytical framework has been specifically designed by Imperial College London to perform this type of analysis. Given that one of the key impacts of large-scale uptake of electro-mobility is expected to be reflected in increased distribution network reinforcement cost, we use our advanced approach to estimating the distribution reinforcement cost on a national scale using the concept of statistically representative networks (described in more detail in Appendix 2). The information on the necessary levels of reinforcement as a function of demand levels in a given scenario is provided as an input into the DSIM model, enabling it to make cost-optimal decisions on the deployment and utilisation of flexible technologies in order to minimise the overall system cost.

Our approach to quantifying the impact of EVs considers total system cost (including both investment and operation) for a given generation and demand scenario, and is capable of comparing the cases when the model is allowed to apply “smart” EV charging strategies and those where charging is not coordinated in any way. The value of smart charging, i.e. the reduction in total system cost as a result of deploying alternative charging strategies will provide valuable insights into the areas where EVs can provide system benefits, potentially helping to shape future commercial and regulatory arrangements so as to enable the efficient mass roll-out of electro-mobility across Europe.

2.2 Scenarios and main assumptions

The backdrop used for our calculations is based on the 2030 European system characterised by significantly reduced carbon emissions as part of the overall European climate change policy and the EU objective to achieve an economy-wide reduction in GHG emissions by 2050 of 80-95% compared to 1990 emission levels. In that context, our analysis is predominantly applied to the “Higher RES” scenario from the European Climate Foundation’s study “Power Perspective 2030” [26].

This chapter also describes the assumptions made with respect to the flexibility of EV charging, i.e. to the capability of EV demand to allow temporal shifting without any compromise on the users’ mobility requirements. These assumptions will also include the capability of flexible EV demand to provide ancillary services to electricity systems, such as frequency regulation.

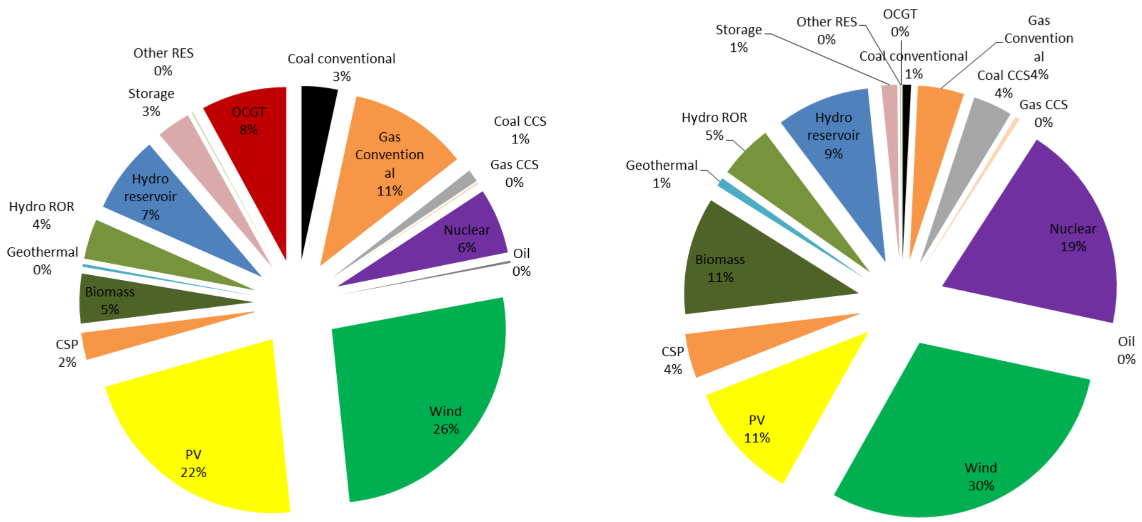
2.2.1 Time horizon

In the studies presented in this report we focus on a mid-term time perspective i.e. on year 2030. This is based on a sufficient lead time to allow for more significant EV uptake levels to materialise in Europe, but also on the structural changes in the European mix of technologies for electricity generation, which is expected to shift significantly towards low- and zero-carbon technologies within the same time window. The mid-term perspective is also well aligned with the Green eMotion vision to develop solutions and technologies that will enable a Europe-wide fully interoperable electro-mobility system within the next decade.

2.2.2 Electricity generation and demand

The assumed evolution of generation capacity in Europe is consistent with the “Higher RES” scenario in the ECF’s Power Perspective 2030 study. According to that scenario, the share of renewables in total annual electricity generation in Europe is around 60%, which is broken into wind (26%), solar (12%), biomass (10%), hydro (11%) and geothermal (1%).[8] The composition of installed generation capacity and expected annual outputs for different technologies in 2030 are shown in Figure 2.1.

[8] OCGT depicted in the figure has the role of backup capacity with very low production level (i.e. close to zero).



a) Installed capacity b) Electricity generation

Figure 2.1 Assumptions on European electricity generation mix in 2030 in terms of: a) generation capacity, and b) annual generation output [26]

In line with the regional representation of the European electricity system depicted in Figure A1.5 (see Appendix 1), where larger countries are represented by multiple nodes i.e. regions. The assumptions on the allocation of installed generation capacity across different countries were made as represented in Figure 2.2. The figure also presents the assumed 2030 peak demand in each country.

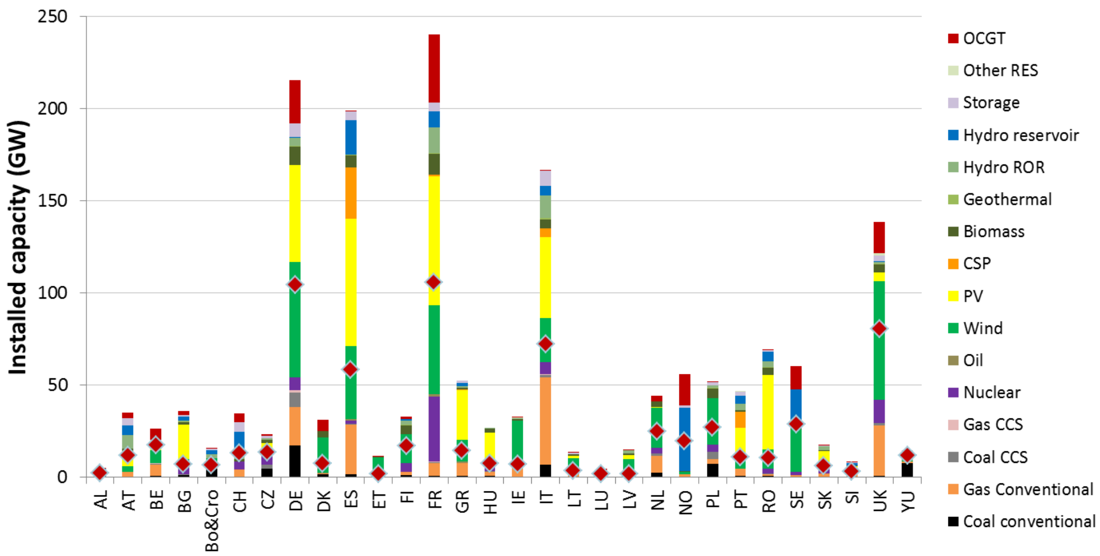


Figure 2.2 Assumptions on generation capacity and peak demand across Europe

Total electricity demand in the European system in 2030 was assumed at 3,985 TWh, while the simultaneous peak demand for the system is 653 GW. This projection is based on the Reference scenario (including policies for 20-20-20 targets) in the European Commission's report “EU energy trends to 2030” [27] and adjusted upwards to reflect fuel shift from transport and heating sectors.[9]

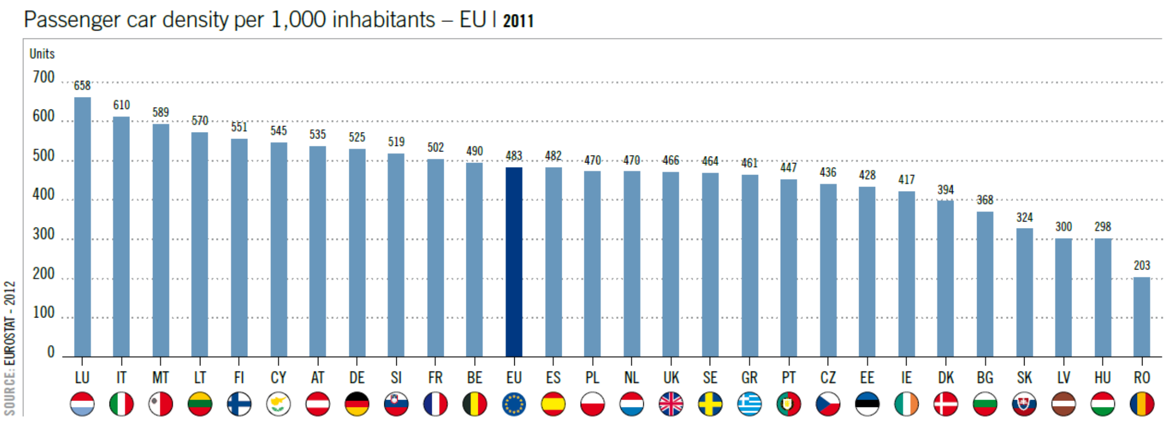
2.2.3 EV uptake level

It is highly uncertain to project the EV uptake in the 2030 horizon. Also, the purpose of our study is to investigate and quantify the impact of electro-mobility on the power system as well as to establish the value of smart EV charging vs. business-as-usual charging. In particular, we are interested in estimating the additional cost of EV demand and potential savings from smart charging *per vehicle*.

In light of this, we assume three different levels of EV penetration in European passenger vehicle fleets, which appear to provide a good range of values that can be expected to be encountered in the 2030 European system:

- Low (5%)
- Medium (15%)
- High (30%)

The reference values used to quantify the numbers of EVs in European passenger vehicle fleets are based on car densities in EU27 countries depicted in Figure 2.3. The numbers depicted are based on data published by the European Automobile Manufacturers Association (ACEA) [28], and are expressed as the number of vehicles per 1000 inhabitants in different countries for year 2011. The average for EU27 was 483 passenger vehicles per 1000 inhabitants, while the densities in individual countries ranged from 658 in Luxembourg to 203 in Romania.



Source: ACEA / Eurostat [28]

Figure 2.3 Passenger cars per 1000 inhabitants in EU27 countries (2011)

The number of vehicles assumed to exist in different European countries in 2030 has been obtained by applying the car densities depicted above and the projected increase in

[9] Demand projection in [27] is based on the PRIMES model, which simulates a market equilibrium solution for energy supply and demand by finding the prices of each energy vector such that the quantity producers wish to supply matches the quantity consumers wish to use.

population calculated by extrapolating the 2009-2013 population trends reported on the World Bank's website.[10]

As elaborated in Appendix 2, the impact of EV deployment on the required investment into distribution network will depend on the type of the network i.e. whether it is located in an urban or rural area. We therefore assume that the distribution of cars across such areas in each country is in direct proportion to the size of the population of these areas.

2.3 Flexibility of EV demand

In our study we assume that if the smart EV charging approach is adopted, a large share of EV demand can be shifted in time towards periods where the cost of supplying this demand would be lower (e.g. night hours with low system demand). In order to quantify the EV demand flexibility, we first note that according to the national travel statistics discussed in Appendix 1 a great majority of vehicles are stationary at any given point in time during a day. This is depicted in an example in Figure 2.4, which represents an average day for a typical passenger vehicle fleet. The percentage of stationary vehicles only drops below 80% during morning and afternoon rush hours (i.e. around 8am and 5pm), while during the night (between midnight and 6am) it is almost 100%.

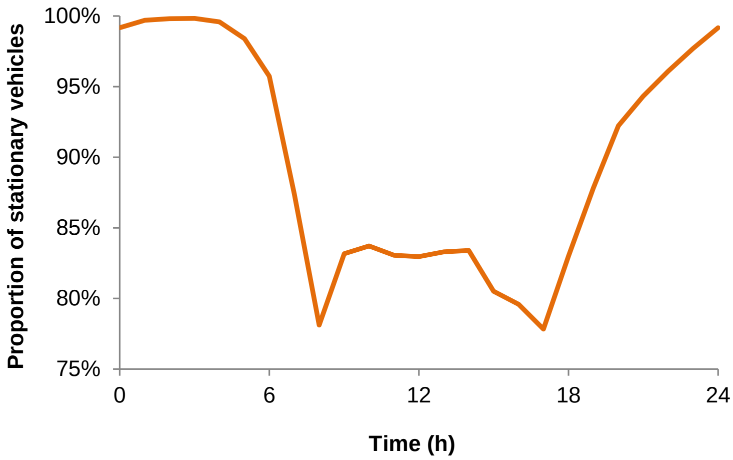


Figure 2.4 Percentage of stationary vehicles during an average day

A relatively high proportion of stationary vehicles, as well as the fact that an average vehicle does not spend more than a few hours per day on the road, suggest that there is considerable flexibility in terms of when the energy required for the EV users' daily journeys can be delivered. In this section we quantify this flexibility by applying bottom-up models of EV demand and charging optimisation, in order to characterise the EVs as flexible demand resource in our whole-system modelling approach.

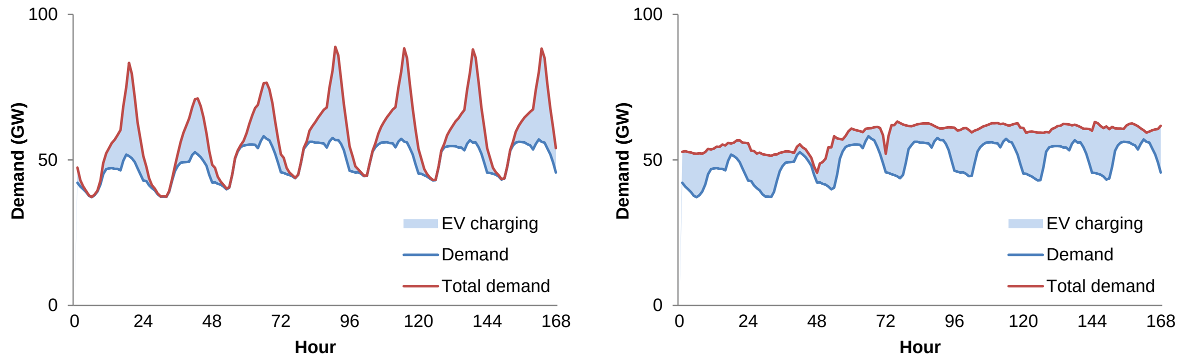
We also acknowledge that due to relatively long stationary times the vehicles could remain connected to their charging point for many hours during the day. During that time, they would be well placed to offer to the system a range of ancillary services. Possibly the most critical of these services will be frequency regulation i.e. primary reserve, which is expected to become a critical aspect of operating future low-carbon systems that are characterised,

[10] http://data.worldbank.org/indicator/SP.POP.GROW

among other things, by greatly reduced inertia provided by rotating masses of synchronous generators.

2.3.1 Capability to shift demand

The example of how EV charging demand can be optimised in order to improve the efficiency of system operation, while respecting the users' mobility requirements ,is given in Figure 2.5. The example is based on the winter peak demand week for the GB system combined with a high EV penetration, and the corresponding case studies carried out in the G4V project [3]. We note the contrast between the user-led charging that leads to extremely high peak demand levels, and smart charging where there is only a modest increase in peak demand. The smart charging profile will obviously require far less peaking generation capacity, as well as lower operating cost due to not having to rely on expensive peaking units.



a) User-led charging   b) Smart charging

Figure 2.5 Comparison between: a) user-led charging; and b) flexible EV demand shifting in order to improve system efficiency

Based on the characteristic journey patterns established as explained in Appendix 1, we estimated the maximum share of EV demand within a given day that can be shifted to other hours while still ensuring timely delivery of energy to allow EV users to complete their normal journeys. Energy shifting would typically involve transferring the EV charging demand towards night hours, when the system demand is low and the system is not operating at its maximum capacity, while at the same time the electricity required by EVs can be supplied at a lower cost. Nevertheless, in systems characterised by a high penetration of intermittent renewable generation such as wind and solar, the EV demand shifting may adapt to the system's specific circumstances by targeting the periods with high wind and solar outputs, which will obviously not coincide with night-time demand troughs.

The percentages of transferrable EV demand have been quantified for different seasons and for workdays versus weekends, and the results are presented in Table 2.1. It is immediately obvious that the share of energy that allows shifting is very high, and exceeds 95% in virtually all cases. We also note that the percentages are the lowest in winter, when it is assumed that the consumption of electricity per kilometre driven is the highest due to vehicle heating requirements. Higher energy requirements also imply less of it can be shifted to other times. During spring, summer and autumn the transferrable share is at or above 99%.

Table 2.1 Percentage of daily EV demand that can be shifted for different seasons and characteristic days

Season	Day type	Percentage of transferrable

		EV demand
Winter	Weekday	95.27%
	Weekend	94.78%
Summer	Weekday	99.09%
	Weekend	98.89%
Spring/autumn	Weekday	99.54%
	Weekend	99.41%

Using the flexibility parameters quantified as above, and feeding them into the DSIM modelling framework, we are capable of determining the optimal decisions with respect to EV demand shifting so that the total system cost is minimised. In other words, rather than moving a major share of EV demand towards the night hours as a rule-of-thumb, the model will decide on an hourly basis how to distribute the EV charging throughout the day in order to optimally respond to cost saving opportunities coming from multiple sources: improved absorption of intermittent renewable output, reducing the necessary generation and transmission capacity, or avoiding distribution network reinforcement triggered by increased local peak demand.

2.3.2 Provision of frequency regulation services

In our modelling approach we also consider the situation where EVs are allowed to contribute to the provision of frequency regulation under the smart charging approaches.[11] Frequency regulation requirements in a system are normally defined by the Transmission System Operator based on short-term dynamic analysis of system behaviour during an unforeseen disturbance (e.g. loss of large generation unit). These requirements are a function of system demand level prior to disturbance, and the nature of disturbance event that the system is expected to successfully withstand. Due to higher inertia provided by the rotational masses of synchronous generators, frequency regulation requirements decrease with higher demand levels. For instance, in the GB system the primary frequency response requirement for the demand level of 35 GW is 800 MW, while at 55 GW this requirement is only about 400 MW.

The need for frequency regulation services, required to deal with sudden frequency drops following a loss of large generating plant, is expected to increase in future electricity systems dominated by non-synchronous renewable generators such as wind and solar. Because of power electronics-based coupling with the grid (unlike synchronous generators) wind generation typically does not provide inertia to the system, leading to more rapid frequency drops following a system disturbance.[12] The aggregate inertia provided by rotating synchronous machines will decrease, increasing the demand for frequency regulation to ensure adequate system performance to maintain the frequency within the statutory limits.

As an illustration for an example future system similar in size to GB, Figure 2.6 presents the necessary levels of primary frequency response to deal with transient (i.e. very short-term) frequency deviations for situations when wind generators are supplying between 0% and 50% of current demand. We observe that the response requirements for the 50% wind penetration effectively double compared to the amount needed at 0% wind.

[11] Frequency regulation as used in this report is equivalent to automatic primary and secondary reserve service.
[12] There is a significant body of research in the relevant literature on techniques that enable wind generators to produce synthetic inertia (cf. [29]); however there is currently no requirement on wind operators to actually provide inertia.

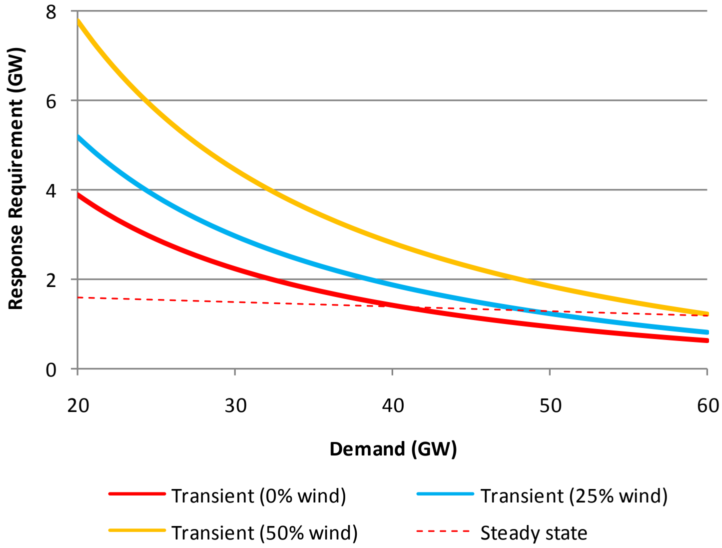


Figure 2.6 Transient and steady-state response requirements for different penetrations of wind capacity

This all suggests that significant additional value could be provided to the future European system if the EVs were capable of delivering frequency regulation services i.e. synthetic inertia by instantly reducing their charging demand in reaction to a fast decline in system frequency. We therefore assume that under a smart charging paradigm various shares of EV demand could be used to provide frequency regulation by rapid disconnection i.e. by interrupting their charging if a major system contingency occurs. This capability does not affect their charging profile (either following BaU approach or smart demand shifting).

Given that it is unrealistic to assume that the entire EV demand is interruptible due to a variety of reasons (users opting out, priority charging etc.), we simulate the following fractions of smart EV demand being able to provide frequency regulation services:[13]

- 0%
- 5%
- 10%
- 15%

It has to be noted that in addition to flexible EV demand there may be other potential frequency regulation providers competing with EVs in the ancillary service markets. These include frequency-sensitive domestic load (such as e.g. smart refrigeration [21]), or more flexible conventional generators that are capable of providing more regulation services than conventional ones with the same capacity. These are however out of scope of our analysis and have not been included in our case studies.

[13] Note that we do not envisage any discharging of electricity from EV batteries into the grid (e.g. V2G concept), which also means that providing frequency regulation using EVs does not imply any reduction in battery life.

2.4 Other assumptions

In this section we specify other assumptions used in our modelling, namely the assumed cost of fuel, carbon and new generation and network capacity.

2.4.1 Fuel cost

The assumed cost of fuel for thermal generation technologies in the 2030 horizon are listed in Table 2.2. The table also includes the assumption on the price of carbon emission allowance in 2030. All fuel and carbon cost assumptions have been taken from the ECF's Power Perspectives 2030 study [26].

Table 2.2 Fuel and carbon cost assumptions in 2030

Fuel type	Fuel price (€/GJ)
Coal	3.18
Gas	9.41
Oil	13.83
Uranium	2.22
Biomass	4.13
Carbon price	€84.6/t

2.4.2 Cost of new generation, transmission and distribution assets

When running the whole-system studies using our DSIM model, we allow the model to add generation capacity to the system if this is necessary to meet the capacity adequacy requirements. It is assumed that the additional capacity is installed in the form of peaking plants such as Open-Cycle Gas Turbine (OCGT) units. Their cost was assumed at the level of around €400/kW.

Assumptions on the cost of transmission and distribution components have been based on a recent report prepared for DG Energy [30]. A summary of cost assumptions for new transmission capacity is provided in Table 2.3, while the cost of distribution cables and lines is presented in Table 2.4 and the cost of transformers and switchgear in Table 2.5.

Table 2.3 Cost assumptions for transmission expansion

Technology	Unit	Costs
Overhead line (AC), normal conditions[(a)]	M€/MW/km	0.50
Overhead line (DC), normal conditions[(a)]	M€/MW/km	0.15
Submarine cable (DC)	M€/MW/km	1.5
Additional costs for rough terrain		35%
Additional costs for extreme conditions		75%
Discount for use of guyed towers		-35%
Converter station (AC/DC)	M€/MW	0.075

[(a)] Including cost of switchgear

Table 2.4 Assumptions on distribution reinforcement costs for cables and overhead lines

Network / Voltage Level (kV)		Overhead (€/m) [(a)]	Cable (€/m)
High voltage (HV)	110 – 123 kV	100 – 260	400 – 1,400
Medium voltage (HV)	30 – 36 kV	50	350
	10 – 20 kV	30 – 50	75 – 140
Low voltage (LV)	0.4 kV	15 – 40	40 – 135

[(a)] Per circuit

Table 2.5 Assumptions on distribution reinforcement costs for transformers and switchgear

Network Level	Secondary Voltage / Assets	Cost
EHV[(1)] / HV	Transformer + switchgear	2,000 – 3,500
HV / LV	30 – 36 kV (transf. + switchgear)	920 – 1,600
	10 – 20 kV (transf. + switchgear)	350 – 1,200
MV / LV	Transformer only	10 – 22
	Station (incl. transf.)	30 – 40

[(1)] Extra high voltage (220 – 380 kV)

2.4.3 Level of market integration

In our studies we assumed a full level of market integration, where none of the European countries is following an energy-neutral or self-sufficient policy. In other words, merit-based exchange of both energy and reserve capacity is allowed across the borders, and countries in the model are allowed to be both net exporters and net importers of electricity.

3 Quantitative results on the economic and environmental impact of EV deployment

In this chapter we apply the whole-system assessment framework described earlier in order to evaluate the economic and environmental impact of additional electricity demand resulting from a mass rollout of EVs in European countries. By comparing the additional cost and emissions observed under different EV charging paradigms, we are also able to establish the economic and environmental benefits of smart EV charging in the context of the expected electricity system decarbonisation.

3.1 Key metrics for studying economic and environmental performance of electricity systems

When evaluating the economic and environmental performance of electricity systems with high uptake of EVs in this report, three principal metrics will be used:

1. Annual system cost
2. Annual volume of renewable energy curtailed
3. Annual carbon emissions

Each one of the three metrics is further elaborated in the following sections.

3.1.1 Annual system cost

Annual cost of the electricity system used to assess its economic performance consists of the following four components:

- *Annualised generation investment cost*: includes the investment cost of additional generation (OCGT) capacity to ensure security of supply in the system.
- *Annualised transmission investment cost*: includes the annualised cost of investing into new transmission and interconnection capacity
- *Annualised distribution network investment cost*: includes the increased investment cost due to higher peak demand in distribution grids.
- *Annual system operation and balancing cost*: includes the fuel and carbon cost associated with running conventional (thermal) generation plants. Renewable generators are assumed to have zero marginal cost, so their output is not explicitly quantified in this category. However, the operating cost will reflect if there is any curtailment of renewable output in the system, as this output will need to be compensated by thermal generation output with the associated fuel and carbon cost.

All investment cost categories (generation, transmission and distribution) are converted from overnight to annualised investment costs assuming the Weighted Average Cost of Capital (WACC) of 7.5% and an assumed equipment lifetime of 20 years.

3.1.2 Renewable energy curtailment

Given that most future scenarios for the evolution of European power systems feature a significant expansion of renewable capacity, ensuring an efficient system integration of (mostly intermittent) renewable resources will be critical to achieve the decarbonisation of the electricity sector at an acceptable cost. On the other hand, balancing the intermittent output of renewable technologies and the largely uncorrelated variations in demand is expected to become additionally challenging in the future, potentially resulting in regular occurrences of renewable output curtailment. Curtailing i.e. constraining off the excess renewable generation may become necessary at a given point in time in order to ensure that the system is balanced while ensuring that adequate levels of ancillary services such as reserve are provided to the system.

Our model is capable of quantifying the necessary renewable curtailment in the system (primarily wind, but also other intermittent renewable technologies such as solar generation). Providing additional flexibility in the system with respect to balancing generation and demand, such as e.g. through enabling flexible charging of EVs, will potentially reduce the necessity to curtail renewable generation, bringing both economic and environmental benefits given that reduced renewable curtailment directly translates into reduced output of conventional generators, i.e. savings in both fuel and carbon cost and reduced emissions.

3.1.3 Carbon emissions

The emissions of carbon dioxide, being the most important greenhouse gas associated with climate change, are quantified in our studies by applying standard emission factors to thermal generation output also taking into the account the efficiencies of thermal generation technologies. The exact impact of EV rollout on the emissions from a given system will depend on the structure of the generation technologies used to supply electricity, in particular the carbon performance of baseline vs. peaking generation plants. Nevertheless, as explained in Section 2.4.1, in our studies we attach a cost to each unit of CO_2 emission, so that the solution found by the model reflects the true socially optimal outcome that takes into account the environmental cost of carbon emissions.

3.2 Assessing the value of flexible EV charging

The focal point of our studies is to assess the value that flexible (smart) EV charging can provide to the system, by generating cost savings across the system, both related to reduced investment into generation and network infrastructure as well as reduced system operating cost. This section described the approach used to quantify the value of flexible EV charging and in particular to express this value in monetary terms per individual (smart) vehicle. This is expected to be critical information for establishing the possible business cases for EV deployment, also having significant repercussions on identifying the barriers to mass EV rollout as well as drafting the policy roadmap to address these barriers.

3.2.1 Non-optimised vs. optimised charging

Our studies compare the annualised system cost levels for various systems and different assumptions on EV penetrations, distinguishing between the two broad groups of cases:

- EV users charge their batteries based only on their convenience i.e. with no regard to the conditions in the system and the cost of providing electricity at a given point in time.
- A certain proportion of EV users opt to allow flexible charging while still ensuring their mobility requirements are not compromised, i.e. delivering electricity to these users can be optimised to support the system. The proportion of EVs in the fleet that allow smart EV demand scheduling is varied between 0% and 100% in 25% steps.

By determining the difference between comparable cases with and without optimised EV charging we can obtain a measure of the value of smart EV demand shifting. If the economic benefits of flexible EV charging (which includes all of the related components of avoided investment and operating cost) are divided with the number of EVs participating in the smart charging scheme, the resulting value per vehicle provides an interesting insight into the possible improvements in commercial performance of EVs in the future system.

3.2.2 Value of providing ancillary services

Section 2.3.2 discussed the motivation behind considering EVs as potential providers of frequency regulation services, both from the aspect of their suitability for this service due to the low level of disruption that this service would impose on EV users, but also due to the rather high expected value attached to this service in future power systems dominated by renewables.

Given the significant expected impact of the ability of EVs to provide ancillary services on their potential value, we include in our case studies cases where various proportions of national EV fleets can provide frequency regulation services to the system, and assess the resulting value for the system in analogy to the previous section – by comparing the difference in system cost between cases with and without frequency regulation provided by EVs, and attributing the savings to those vehicles contributing to ancillary services.

3.3 Results of economic assessment for selected European countries

In this section we present the quantitative assessment of the economic performance of electricity systems in several European countries against different assumptions on the EV deployment and the share of EVs participating in smart charge scheduling schemes. For each country (or pair of countries) for which a set of studies has been run we first present the detailed breakdown of generation capacity as assumed in the 2030 scenario used in the report. This is followed by evaluating the additional annualised system cost for various rates of EV penetration and participation in smart demand shifting. The final set of results presented for each system quantifies the value i.e. the benefit for the system created from participation of EVs in frequency regulation.

3.3.1 Germany and Denmark

In the assumed 2030 scenario German and Danish systems are dominated by wind (contributing almost 80% of total generation capacity in Denmark and 34% in Germany) and PV generation (almost 30% in Germany). The rest of the capacity mix consists of biomass, conventional coal and gas generation, and some CCS (9 GW) and nuclear (7 GW) capacity in Germany. The assumed composition of German and Danish electricity generation portfolio in 2030 is presented in Figure 3.1.

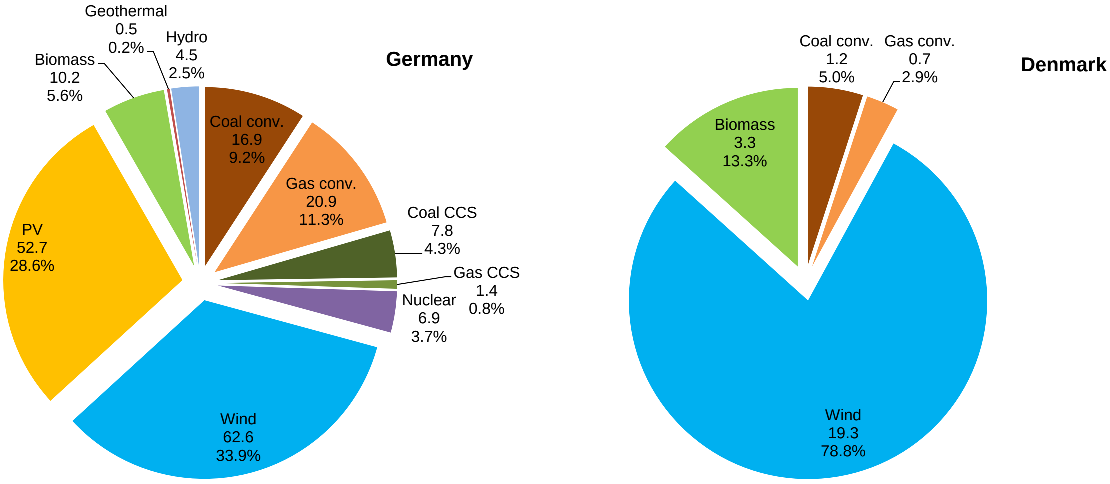


Figure 3.1 Assumed generation capacity mix in Germany and Denmark in 2030 (in GW)

Increase in total system cost

The increase in annualised system cost caused by the deployment of EVs in Germany and Denmark is presented in Figure 3.2. The layout of the figure (also followed for other countries later in this section) is as follows.

Three EV penetration levels are presented (as discussed in Section 2.2.3), Low (5%), Medium (15%) and High (30%). For each of these penetration levels, the share of EVs participating in smart demand shifting is varied between 0% and 100% in 25% steps. For each EV penetration and each smart participation rate the additional annual cost to the electricity system is quantified and broken down into the four key components: three CAPEX categories (generation, transmission and distribution) and annual operating cost (OPEX), associated with fuel and carbon cost. Due to the obvious difference in scale between the incremental cost for Low and High EV penetrations, the cost results in the former case are also enlarged in the upper left part of the chart. Finally, for each EV penetration and 0% and 100% smart participation rates additional total cost points are plotted that represent the system cost reduction when 15% of EVs participate in frequency regulation (FR).

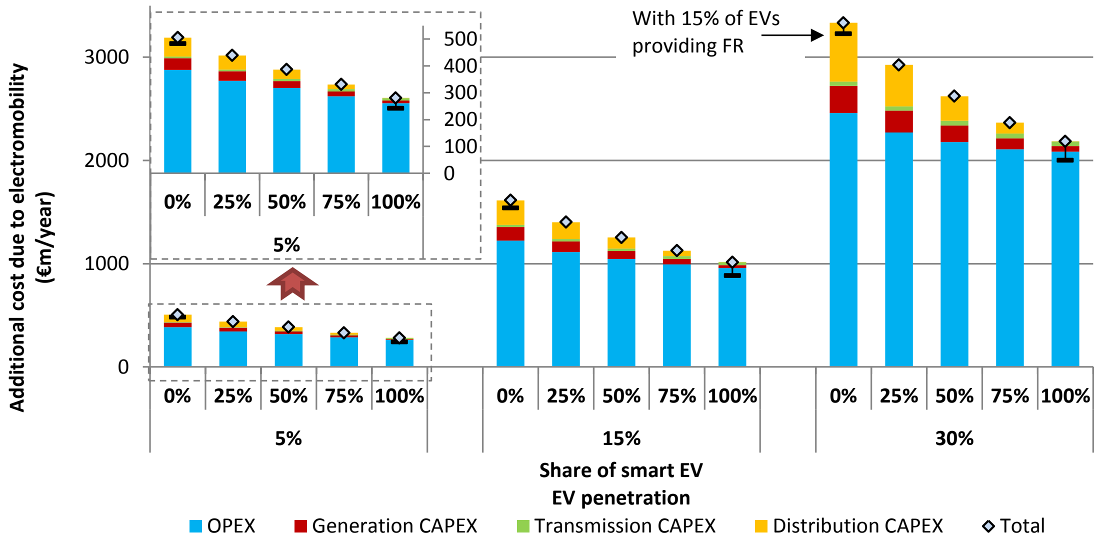


Figure 3.2 Additional annualised system cost due to EV deployment in Germany and Denmark in 2030

In the case of Germany and Denmark, we observe that the annualised system cost increases by €0.5bn, €1.6bn and €3.3bn in Low, Medium and High penetration cases, respectively, if no smart charging takes place. As the share of smart EV demand shifting increases we observe a progressive decrease in system cost, so that for 100% of smart timing the additional system cost in Low, Medium and High penetration cases is reduced by 45%, 37% and 35%, respectively.

Another observation is that the largest component of additional system cost due to EV deployment is the increase in OPEX, i.e. fuel and carbon cost. OPEX increase makes up about three quarters of total additional cost in 0% smart cases across all penetrations. The remaining cost components with no smart charging are (in decreasing order): distribution CAPEX (14-17%), generation CAPEX (8-9%) and transmission CAPEX (about 1%).

We further note that with increasing proportions of EVs participating in smart demand shifting all cost components diminish, but in different proportions. All CAPEX cost categories drop to virtually zero, while the OPEX component reduces by 32%, 22% and 15% in Low, Medium and High penetration scenarios, respectively. The effect of reduced CAPEX with high smart participation rates is a direct consequence of smart EV charging being capable of reducing peak demand i.e. redistributing EV demand in time, as discussed earlier (see e.g. Section 2.3.1), so that the additional energy required by EVs is supplied with virtually the same capacity as without the EVs present on the system. On the other hand, a flatter demand profile requires lower usage of high marginal-cost plants, and is also beneficial for absorbing renewable generation, both of which contributes to considerable OPEX reductions for increasing smart shifting participation rates.

Finally, it is possible to note the impact of FR provision by EVs on the cost of supplying the EV demand. We note that for the 0% smart shifting case the FR provision reduces the incremental system cost by only 3-5% for all penetration scenarios, while the cost reductions in the 100% smart shifting case are 14% (Low), 13% (Medium) and 8% (High). This result suggests that there is a certain synergy between smart demand shifting and FR provision by EVs, i.e. that the value of both services combined is greater than the sum of the value of services provided separately of each other. We note that the key factor contributing to the increased value of FR provided by EVs when vehicles also participate in smart shifting is the fact that with smart scheduling their demand is spread much more evenly over the day. Given that we assume that EVs can provide FR through short-lived interruptions in charging, this means that they are also able to provide a more constant level of FR throughout the day and that less FR needs to be provided by conventional generators.

Costs and benefits per EV

When additional cost to supply EV demand across various scenarios is divided with the number of EVs assumed to exist in the system, we obtain the additional system cost per vehicle. Figure 3.3 compares how the incremental cost per EV changes between different EV penetrations and different shares of smart charge scheduling in the German-Danish system.

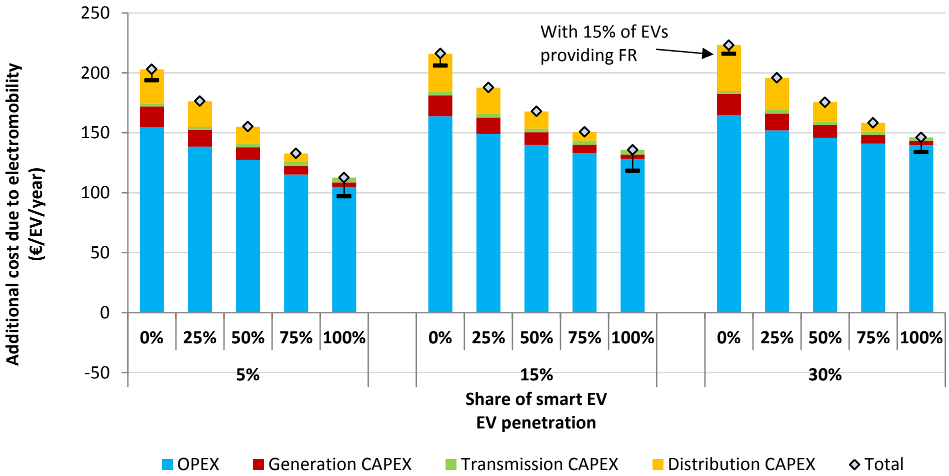


Figure 3.3 Additional system cost per EV in Germany and Denmark in 2030

The additional cost per EV according to Figure 3.3 varies between €203 and €223 per annum in the non-smart case, with slightly higher cost levels associated with higher EV penetrations. Having a fully smart charge scheduling reduces the incremental cost to between €113 and €146/EV/year (higher cost is again attributable to higher EV penetrations). In relative terms, the incremental cost of EV integration is thus reduced by 35-45% compared to the BaU case. A further reduction of €12-17/EV/year can be achieved with 15% of EVs participating in FR provision, lowering the total incremental cost in the fully smart case to €97-134/EV/year, i.e. 40-52% less than in the BaU case.

We further explore the benefits i.e. savings from smart EV demand shifting from the perspective of an individual vehicle partaking in smart control. To that end, the total benefit of smart demand shifting (equal to the cost difference between the scenarios with and without smart demand shifting for a given penetration level) is expressed in Figure 3.4 as avoided annualised system cost per single EV that participates in smart demand shifting.

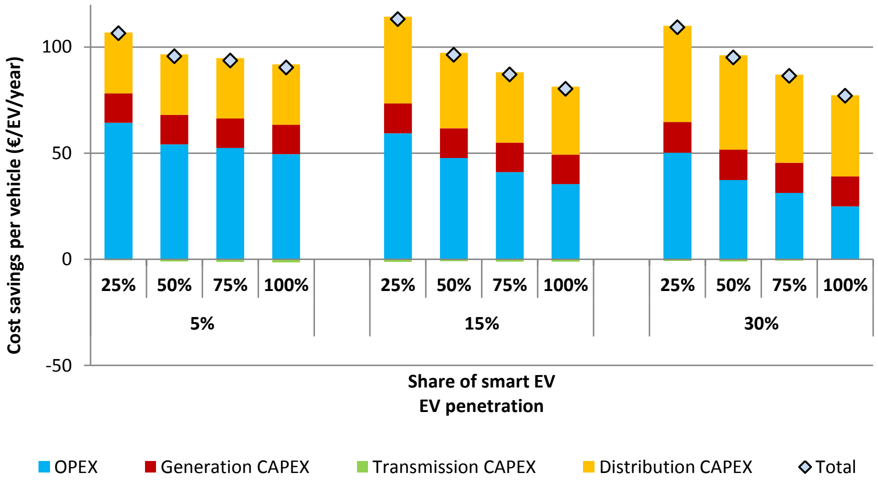


Figure 3.4 Cost savings from smart EV charging in Germany and Denmark in 2030

The total value of annualised system cost savings per EV are €90-106 for Low, €80-113 for Medium and €77-109 for High EV penetration. We further note that the value per single EV consists of three major components: (i) OPEX savings, and reduction in (ii) distribution and (iii) generation CAPEX.

OPEX generally represents the largest component, although its magnitude decreases with increasing EV penetrations and smart shifting participation rates. At Low EV penetration the OPEX savings per EV vary in the range of €50-64 per annum; this value drops to €35-59 for Medium and €25-50 for High penetration, suggesting higher sensitivity to smart shifting participation rate at higher EV penetrations. In other words, we observe a saturation effect with respect to OPEX savings with increasing number of EVs participating in smart demand scheduling schemes.

Generation CAPEX savings on the other hand show very little variation regardless of the penetration rate and smart EV share, while and are relatively stable around the value of €14 per EV annually. Distribution part is more sensitive to the EV penetration level, so that the savings are found to be around €28.5 for Low, €32-41 for Medium and €38-45 per EV per annum for High penetration. Obviously, with diminishing opportunities to generate OPEX savings, more flexibility from smart EVs is utilised to mitigate distribution network reinforcement cost. We observe no significant impact of smart EV charging on transmission CAPEX savings for the German-Danish system.

Finally, the value of EVs providing FR at different penetrations in both smart and non-smart cases is quantified in Figure 3.5. An immediately obvious conclusion is that the economic benefits of providing this ancillary service is almost exclusively attributable to savings in OPEX. This is not surprising, given that the key benefit of EVs providing frequency regulation is that conventional generators are no longer required to operate at lower efficiency; hence the savings in fuel and carbon cost (i.e. OPEX).

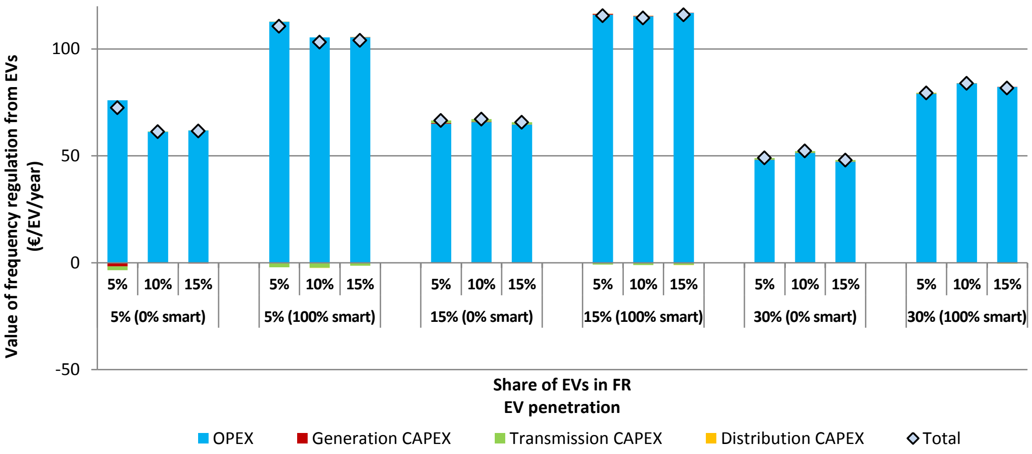


Figure 3.5 Cost savings from FR provision by EVs in Germany and Denmark in 2030

As mentioned earlier, the results suggest a synergy between FR provision and smart charge scheduling – the value of EV-based FR is €80-115 per EV annually when combined with smart demand shifting, while in the absence of this the value is only about €48-72/EV/year. This is because the smart scheduling spreads the EV demand more evenly across the day, enabling a more continuous provision of FR during the day and hence maximising the value of capability to provide FR.

3.3.2 Spain

According to the 2030 scenario assumed in this study, the generation capacity in Spain in this year will be predominantly renewable: about 20% will be wind, some 35% PV generation, around 15% CSP and 13% other renewables (mostly hydro and biomass). Conventional sources will make up only about 16% of total generation capacity, and the bulk of it will be gas generation. Figure 3.6 shows graphically the assumed breakdown of Spanish generation capacity mix by technology in 2030.

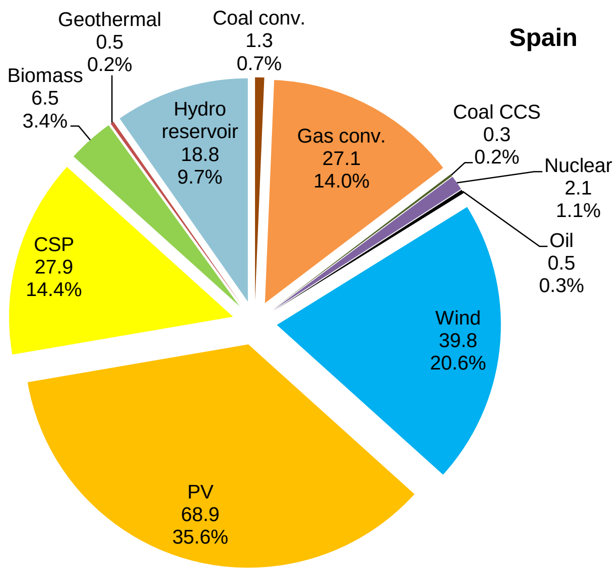


Figure 3.6 Assumed generation capacity mix in Spain in 2030 (in GW)

Increase in total system cost

The incremental annualised system cost caused by the deployment of EVs in the Spanish system is presented in Figure 3.7, following the same layout as in Figure 3.2.

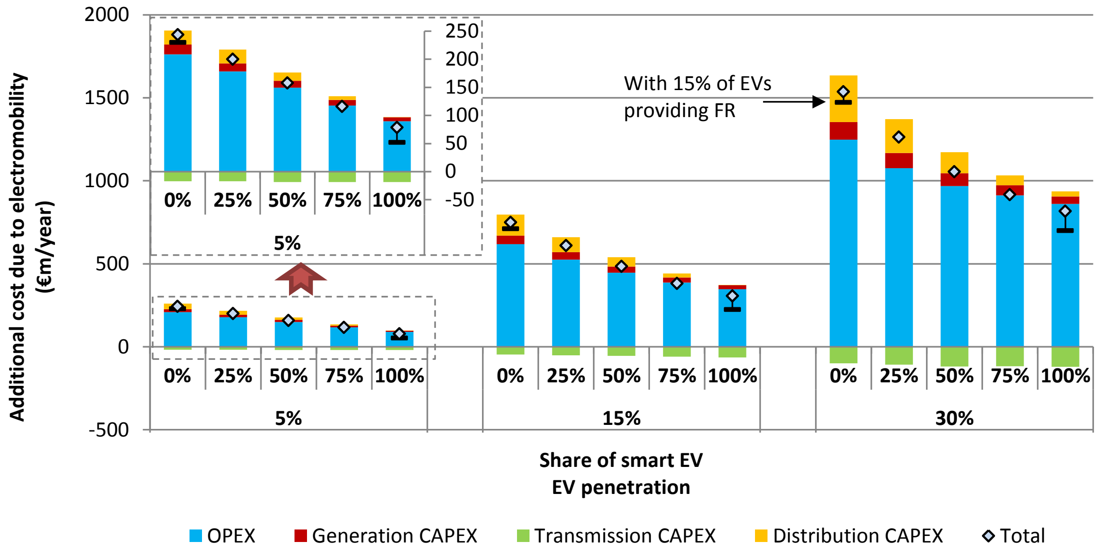


Figure 3.7 Additional annualised system cost due to EV deployment in Spain in 2030

The case studies carried out suggest that the annualised system cost in Spain for the non-smart charging cases increases by €0.24bn, €0.75bn and €1.54bn in Low, Medium and High penetration cases, respectively, following a broadly linear trend with respect to EV penetration. As in the previous case, the increasing share of smart demand shifting results in a progressive decrease of system cost. At 100% of smart scheduling the additional system cost is reduced by 68%, 59% and 47% compared to no smart charging in Low, Medium and High penetration cases, respectively.

The largest component of additional system cost is again the increase in OPEX (fuel and carbon cost), accounting for 81-86% of total additional cost in 0% smart cases across different penetrations. The remaining cost components with no smart charging are distribution CAPEX (14-18%) and generation CAPEX (7%). In the case of Spain we observe that EV deployment results in a reduction of transmission CAPEX at the level of 6-7% of total additional cost. This suggests that additional demand associated with EVs has the effect of balancing out geographically the electricity demand in Spain, reducing the need to invest in new transmission capacity to transfer electricity from regions that are net producers to those that are net consumers.

An increasing proportion of smart scheduling reduces all cost components in a broadly linear fashion. As before, CAPEX cost categories drop to virtually zero due to the ability of smart demand shifting to mitigate the increase in peak demand. The OPEX component reduces as well (although not to zero) by 57%, 44% and 31% in Low, Medium and High penetration scenarios, respectively. This follows from a lower usage of peaking plants and less renewable curtailment with increasing smart participation rates.

Benefits of FR provision by EVs are even more pronounced than in the previous case. At 0% smart the FR provision reduces the incremental system cost by 4-6%, while the cost reductions in the 100% smart case are 34% (Low), 27% (Medium) and 14% (High). We observe again the synergy between smart scheduling and FR provision by EVs, i.e. the enhanced value of both services when provided in combination. The high value of FR combined with smart scheduling in the case of Spain is driven by the higher efficiency losses in the baseline case when FR is provided by offloading gas generators (unlike the mix of gas and coal in the case of Germany and Denmark).

Costs and benefits per EV

The incremental system cost per EV is depicted in Figure 3.8 for various cases analysed for the Spanish system. In the non-smart (BaU) case this cost is found to be in the range of €186-195/EV/year, with the value slightly increasing towards higher EV penetrations. 100% share of smart EV demand shifting brings the incremental cost down to €60-104/EV/year (lower cost is observed for lower EV penetrations and vice versa), or 47-68% lower than in the BaU case. FR provision from EVs further reduces the incremental cost to €40-89/EV/year, so that in the fully smart case the additional cost is only 21-46% of the incremental cost in the BaU case.

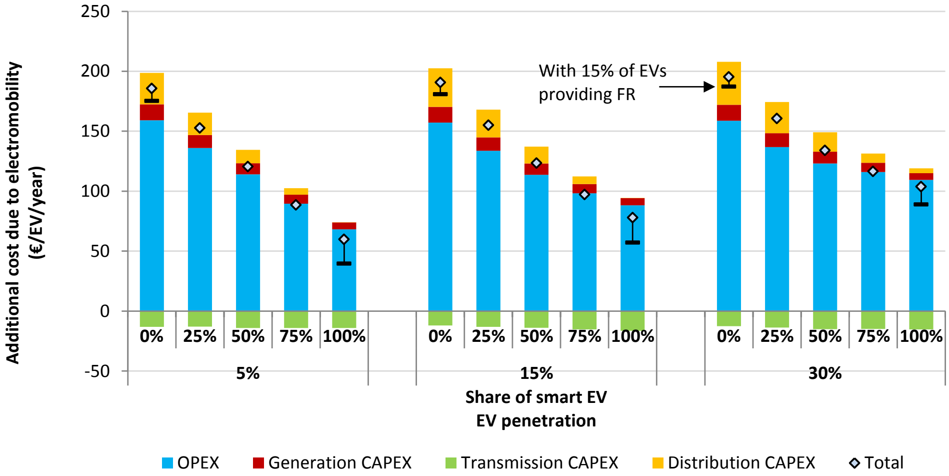


Figure 3.8 Additional system cost per EV in Spain in 2030

The benefits of smart EV scheduling in the Spanish system are expressed per individual vehicle in Figure 3.9. Total value of savings per EV is relatively stable at Low penetration (around €130/EV/year), while at Medium and High penetrations there is a notable decline in benefit per EV with increasing smart participation share (€143 to €113 per EV in Medium, €138 to €91 per EV in High penetration case). The major observed components of value per EV are OPEX savings and reduction in distribution, transmission and generation CAPEX.

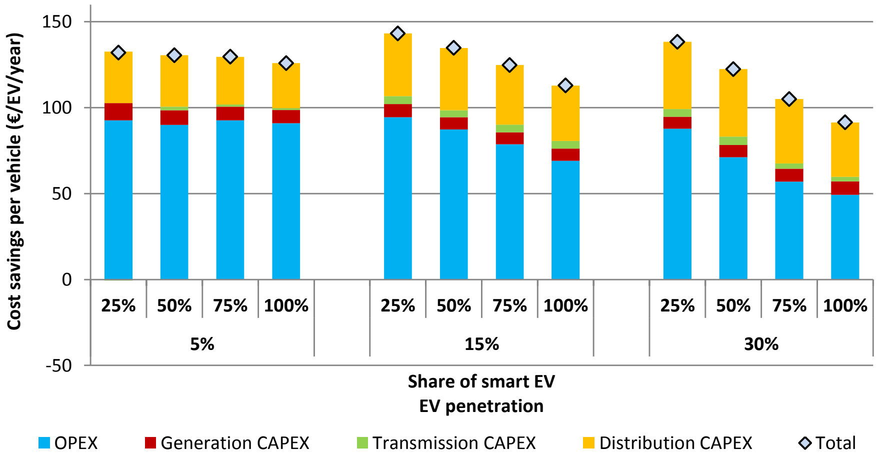


Figure 3.9 Cost savings from smart EV charging in Spain in 2030

OPEX is the dominant savings component, at around €90-92/EV/year at Low, €69-94/EV/year at Medium and €49-88 per EV in High penetration case. There is again a saturation effect, in particular at High penetration, where the value of OPEX savings diminishes with increasing smart EV share. Distribution CAPEX savings are not very sensitive to the share of smart charging, but on the other hand increase at higher EV penetrations (€26-30/EV at Low, €32-36/EV at Medium and €32-39/EV at High). The generation CAPEX savings component is relatively stable at the level of €7-10 per EV annually, although there is a decreasing trend towards higher penetrations.

The impact on transmission CAPEX is mixed: at very low rates of EV deployment and low shares of smart scheduling the value of transmission investment savings may even be negative (up to €1/EV/year of cost increase), while at higher penetration levels the value of being smart is positive (€3-5/EV/year). This can be explained by the volume of EVs as a flexible resource: at low penetration smart charging requires reinforcement in transmission grid in order for the EV-based flexibility to support system operation in all Spanish regions. At high penetrations, the need to reinforce transmission network diminishes and even reverses, so that more electricity is used locally requiring less transmission capacity than in the case without EVs. All these effects are however marginal compared to potential savings in OPEX and distribution CAPEX.

The economic benefits of FR provision by EVs in the Spanish system are quantified in Figure 3.10. Two effects can be observed, as in the previous case: (i) the value of FR is almost exclusively attributable to savings in OPEX; and (ii) there is synergy between smart scheduling and FR provision. In cases with no EV demand scheduling the value of FR provision never exceeds €74/EV/year, while in combination with smart demand shifting this increases to between €100/EV/year (High penetration) and €150/EV/year (Low and Medium penetrations). When combined with savings from smart charging presented in Figure 3.9, the total value per EV that both provides FR and participates in smart charging could reach up to €270/EV/year.

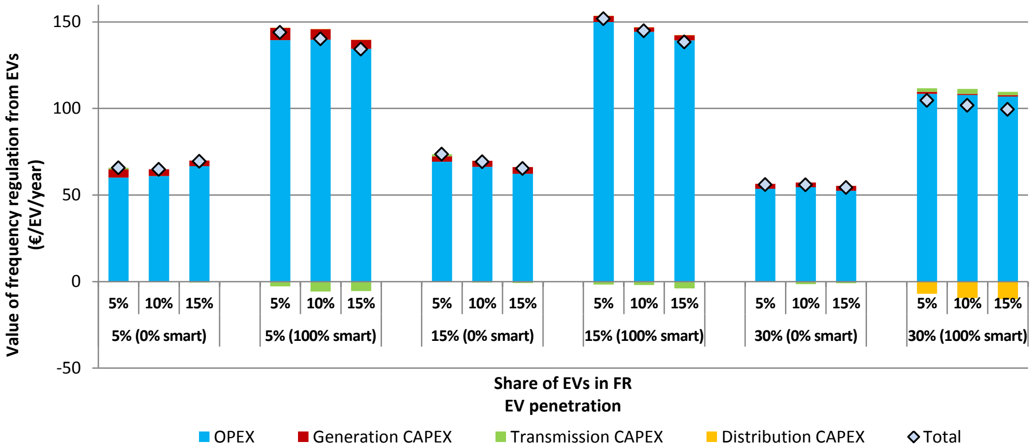


Figure 3.10 Cost savings from FR provision by EVs in Spain in 2030

3.3.3 Italy

Generation capacity in Italy in 2030 is assumed to consist of about 40% of non-renewable generation, three quarters of which is gas and the rest nuclear and coal. The remaining capacity is mostly made up of wind (15%), PV (28%) and hydro (11%), with other technologies present in smaller proportions. The structure of the generation capacity for Italy in 2030 is illustrated in Figure 3.11.

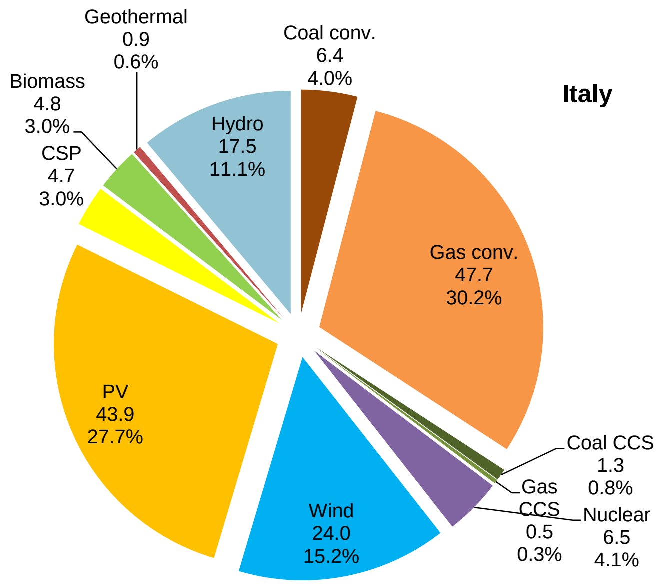


Figure 3.11 Assumed generation capacity mix in Italy in 2030 (in GW)

Increase in total system cost

Additional annualised system cost caused by the introduction of EVs in the Italian system is presented in Figure 3.12.

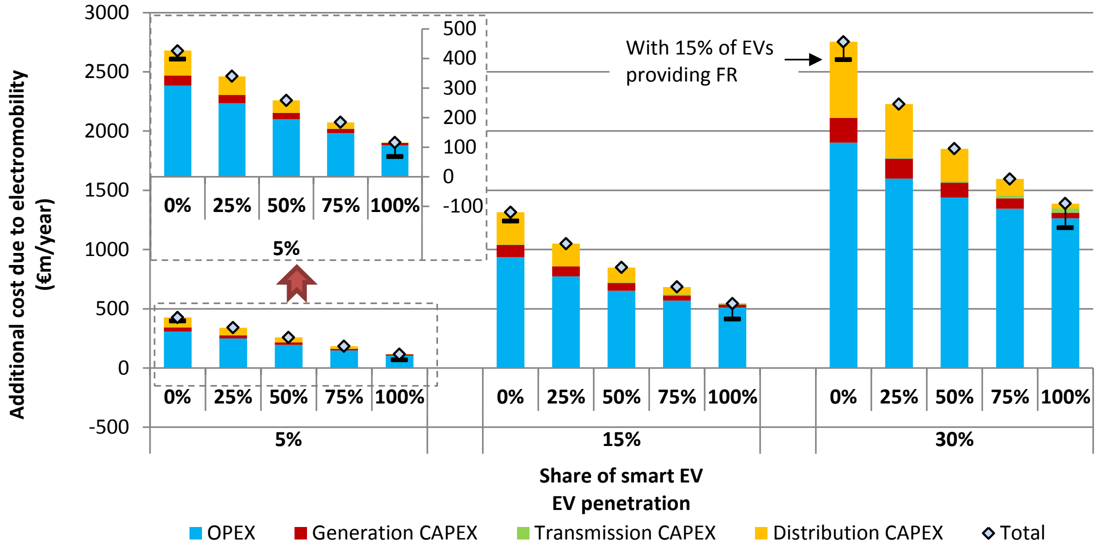


Figure 3.12 Additional annualised system cost due to EV deployment in Italy in 2030

Annualised system cost in Italy for the cases without smart charging grows by €0.43bn, €1.31bn and €2.75bn in Low, Medium and High penetration cases, respectively, with the cost increasing in linear proportion to the EV penetration. Increasing the share of smart EV charging brings about a progressive decline in system cost: at 100% of smart the additional system cost drops by 73%, 59% and 50% compared to the 0% smart case for Low, Medium and High penetration cases, respectively.

As in the other systems, the largest component of additional system cost is the OPEX (fuel and carbon cost), accounting for 69-72% of total additional cost in 0% smart cases across different penetrations. Other cost categories (in the 0% smart case) include distribution CAPEX (20-23%) and generation CAPEX (8%). No significant impact on the transmission investment cost is observed in the case of Italy.

Increasing the share of smart charging reduces all cost components linearly, and as before CAPEX cost categories drop to virtually zero at 100% smart share. The OPEX component on the other hand reduces by 65%, 45% and 34% in Low, Medium and High penetration scenarios, respectively, when moving from 0% to 100% smart. The effect is relatively similar to what has been observed for the previous two systems.

Cost reduction due to FR provision by EVs is around 5.5-7% at 0% smart, while in the 100% smart case the reduction is 41% (Low), 24% (Medium) and 15% (High). There is again an evident synergy between smart charging and FR provision by EVs.

Costs and benefits per EV

Figure 3.13 shows the incremental system cost per EV across different scenarios analysed for the Italian system. The additional cost per vehicle in the non-smart (BaU) case varies within the range of €203-219/EV/year, while for 100% share of smart EV demand shifting this reduces to €55-110/EV/year (50-73% lower than in the BaU case). Additional reduction in the incremental cost is observed in the case of FR provision from EVs, bringing the cost to €32-94/EV/year (only 16-43% of the BaU incremental cost), with the lower cost levels being observed for low EV penetration levels.

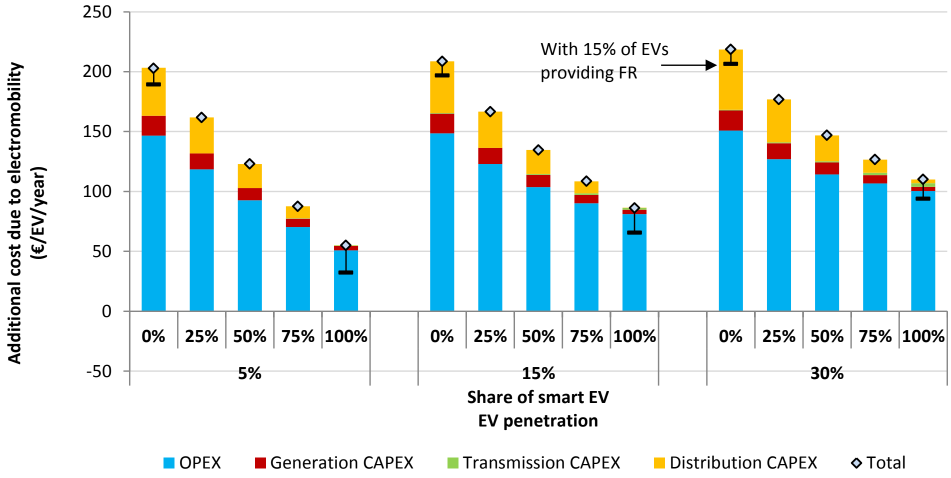


Figure 3.13 Additional system cost per EV in Italy in 2030

Figure 3.14 presents the benefits of smart EV scheduling in the Italian system per individual EV. Total value of savings per EV varies between €148-164 per EV per annum for Low, €122-168 for Medium and €108-167 for High penetration. Economic value per EV is again dominated by OPEX savings and reduction in distribution and generation CAPEX (transmission CAPEX is only marginally present).

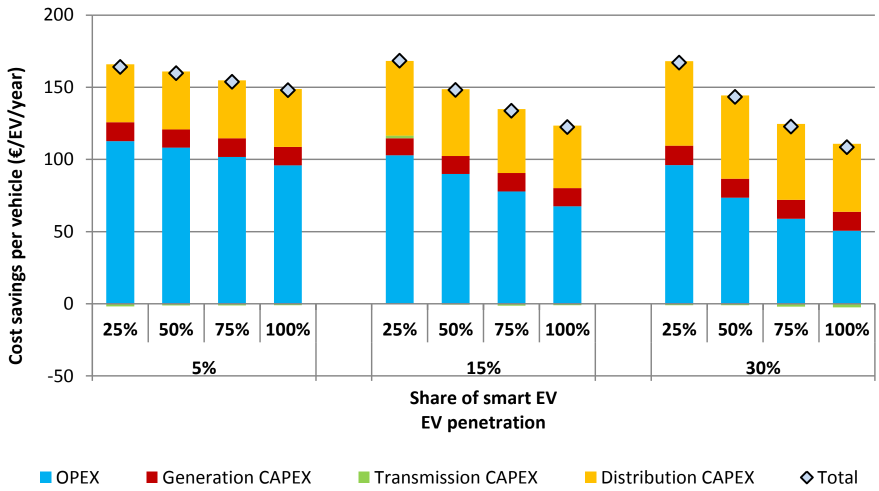


Figure 3.14 Cost savings from smart EV charging in Italy in 2030

The bulk of cost savings per EV is made up of OPEX savings, which are found to be €96-113 per annum in Low, €68-103 in Medium, and €51-96 per annum in High penetration case. It is again possible to observe a saturation effect at Medium and High penetration levels, i.e. the value of OPEX savings diminishes with increasing smart EV share. Nevertheless, in all cases OPEX savings contribute to overall savings with at least about 50%.

Distribution CAPEX savings are a function of penetration level and smart share: €40/EV at Low, €43-52 in Medium and €47-59/EV in High penetration case (higher values in these ranges correspond to lower smart shares and vice versa). Generation CAPEX savings vary relatively little between different cases, and are at the level of around €13 per EV annually. The impact on transmission CAPEX is largely negligible.

Figure 3.15 quantifies the cost savings from EVs providing FR in the Italian system. Similar to the previous cases, the value of FR is almost exclusively composed of OPEX savings, while there is at the same time synergy i.e. higher economic value of FR provision when combined with smart scheduling. In cases with 0% smart scheduling the value of FR provision varies in the range of €75-95/EV/year, while for 100% smart scheduling the value increases to €78-182/EV/year, resulting in a high combined value of up to €330/EV/year when savings from smart scheduling are also taken into account.

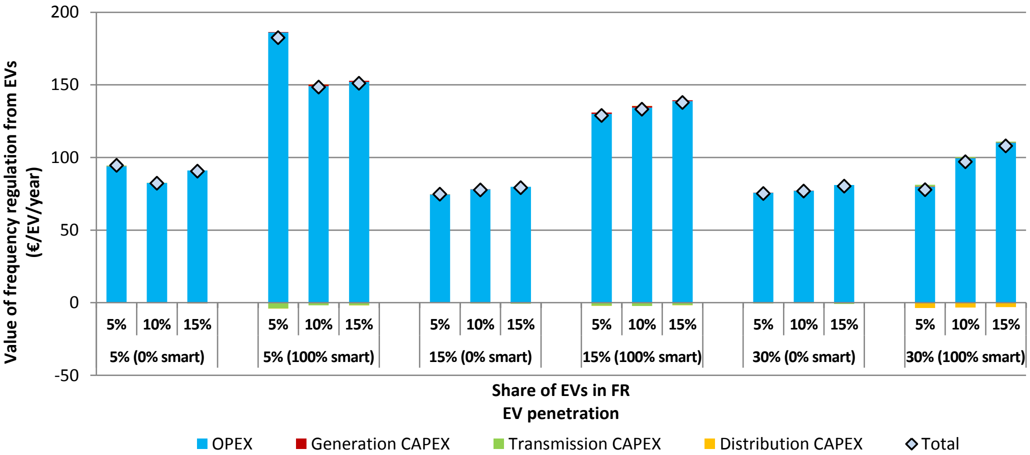


Figure 3.15 Cost savings from FR provision by EVs in Italy in 2030

3.3.4 United Kingdom and Republic of Ireland

In line with their abundant wind energy potential, the UK and the Republic of Ireland (RI) are assumed to be characterised by very large installed wind capacity in 2030 – about 65 GW in the UK (55% of total capacity) and 25 GW in Ireland (80% of total). Other renewable technologies are present in smaller proportions, while conventional technologies comprise gas generation in both UK and Ireland (23% and 15% respectively), and nuclear in the UK (10.5% of the total UK capacity). Generation capacity portfolios for both countries in 2030 are shown in Figure 3.16.

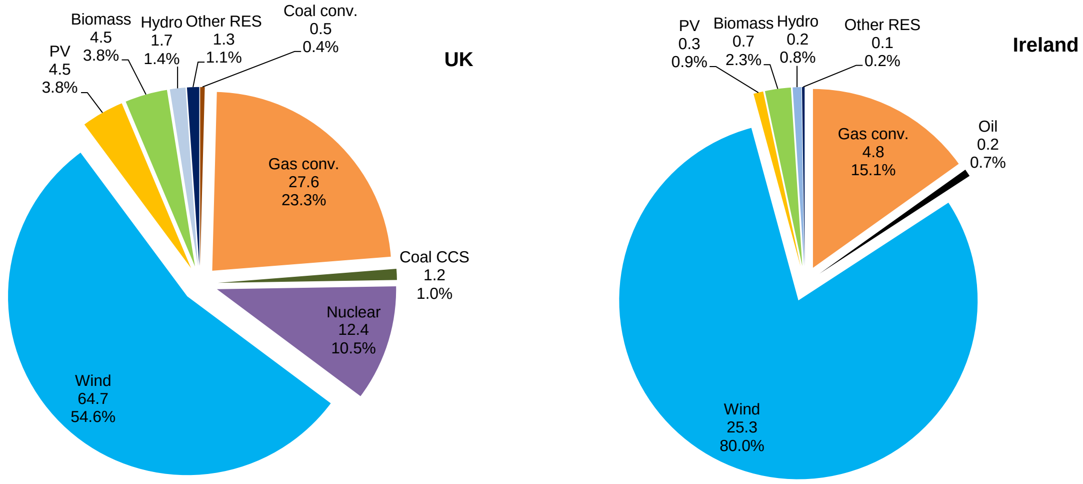


Figure 3.16 Assumed generation capacity mix in the UK and Ireland in 2030 (in GW)

Increase in total system cost

Following the same presentation approach as for the other systems, the incremental annualised system cost caused by the deployment of EVs in the combined UK-RI system is presented in Figure 3.17.

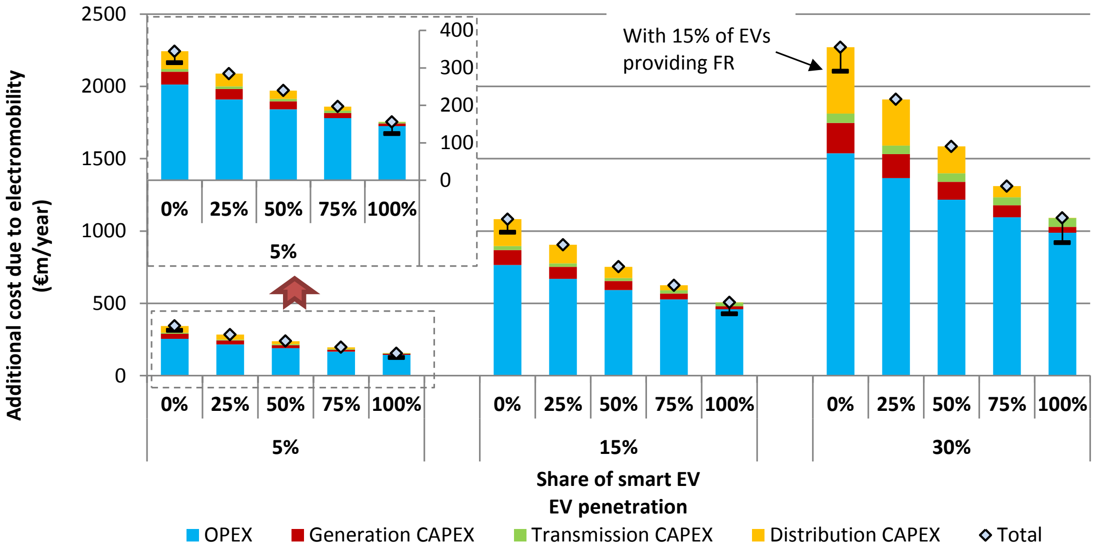


Figure 3.17 Additional annualised system cost due to EV deployment in the UK and Ireland in 2030

The annualised system cost in the UK and RI required to supply the new EV demand in the non-smart charging cases increases by €0.34bn, €1.08bn and €2.27bn in Low, Medium and High penetration cases, respectively. We again note that the trend of cost increase is broadly linear with respect to EV penetration. As the share of smart EV demand scheduling increases, we observe a steady decline in additional system cost. At 100% smart scheduling the additional cost is reduced by 52-55% compared to the non-smart charging case. This represents a significant cost reduction potential that can be captured by adopting smart charging schemes.

The dominant component of additional system cost by far is again the increase in OPEX, contributing about 68-74% of total additional cost in 0% smart cases across different penetrations. Other significant cost components in the 0% smart case include distribution CAPEX (14-20%) and generation CAPEX (9-10%). Transmission CAPEX is the smallest component at about 2-3% of the total incremental cost in all 0% smart cases.

Progressive introduction of smart charge scheduling reduces all cost components in a broadly linear fashion. All CAPEX cost categories are effectively reduced to near zero due to the ability of smart EV scheduling to greatly reduce the increase in peak demand. The OPEX component reduces by 43%, 40% and 36% in Low, Medium and High penetration scenarios, respectively. OPEX reduction due to from smart charging follows from a lower usage of peaking plants and less renewable curtailment.

Cost reduction due to FR provision by EVs at 0% smart is 7-9%, while in the 100% smart scheduling case the cost drops much more significantly in relative terms (although in absolute terms the cost reduction effect is similar): 20% (Low), and 16% (Medium and High).

The combination of smart scheduling and FR provision by EVs yields an enhanced value of both services for this system as well.

Costs and benefits per EV

The incremental system cost per EV across different scenarios analysed for the UK-RI system is shown in Figure 3.18. In the non-smart (BaU) case the additional cost per vehicle is found to be in the range of €182-200/EV/year, with higher values observed at higher EV penetrations and vice versa. 100% share of smart EV demand shifting reduces the incremental cost to €82-96/EV/year, which is 52-55% lower than in the BaU case. FR provision from EVs further reduces the incremental cost to €66-81/EV/year, making the incremental cost in the fully smart case only 36-41% of the cost in the BaU case.

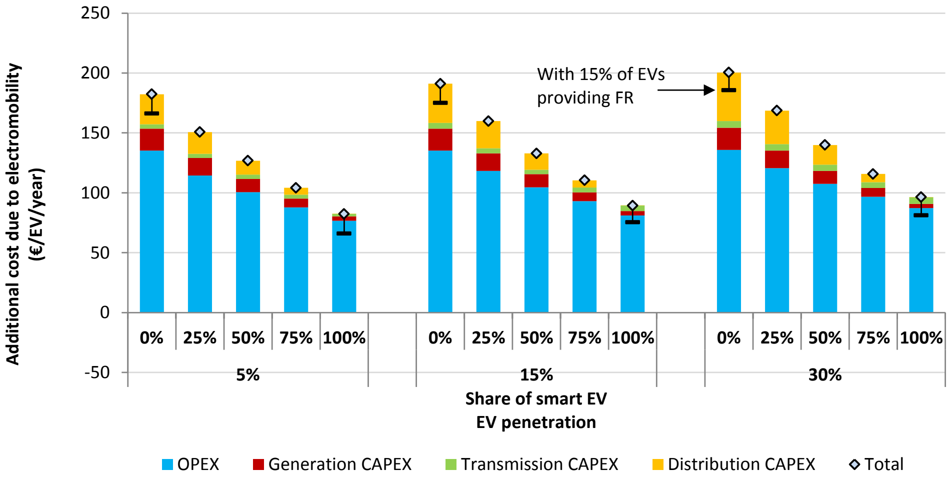


Figure 3.18 Additional system cost per EV in UK and Ireland in 2030

The benefits of smart EV scheduling per single EV in the UK-Irish system are presented in Figure 3.19. We note that the value drops with increasing shares of smart participation, but varies very little across different penetrations. The observed value per vehicle is in the range of €100-127/EV/year. The major components of value per EV are OPEX savings and reduction in distribution and generation CAPEX, and their proportions change depending on the EV penetration and smart scheduling shares.

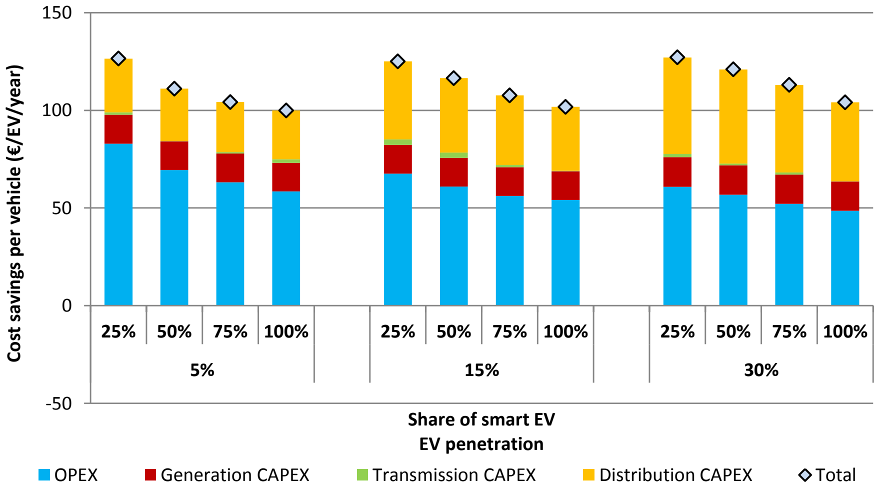


Figure 3.19 Cost savings from smart EV charging in the UK and Ireland in 2030

OPEX savings represent the largest component, although their magnitude decreases with increasing EV penetrations and smart charging participation rates. At Low EV penetration OPEX savings per EV vary in the range of €58-83 per annum; this value drops to €54-68 for Medium and €49-61 for High penetration. These figures suggest a saturation effect with respect to OPEX savings with increasing number of EVs participating in smart demand shifting schemes.

Generation CAPEX savings are virtually constant at the level of €15/EV/year, suggesting that each EV participating in smart scheduling is able to displace a similar amount of generation capacity regardless of the EV penetration. Distribution CAPEX savings also show little variation with respect to the smart EV share, but tend to increase at higher EV penetrations: €25-28 at Low, €33-40 at Medium and €40-49 per EV per annum for High penetration. There is only a minor impact (in the order of €1-3/EV) of smart EV charging on transmission CAPEX savings for the UK-Ireland system.

The cost savings resulting from FR provision by EVs in the UK-RI system are presented in Figure 3.20. Similar to the previous cases the value of FR is almost exclusively made up of OPEX savings. On the other hand, there is a much less pronounced effect of synergy between FR provision and smart charge scheduling. The values observed vary rather symmetrically around €100/EV/year (between about €60 and €140). We further observe that in the 100% smart cases the provision of FR also requires additional investment into transmission network. This occurs as the result of EV demand flexibility being made available to all regions in the system, including those with potentially lower number of EVs but higher flexibility requirements due to high wind capacity (e.g. Scotland).

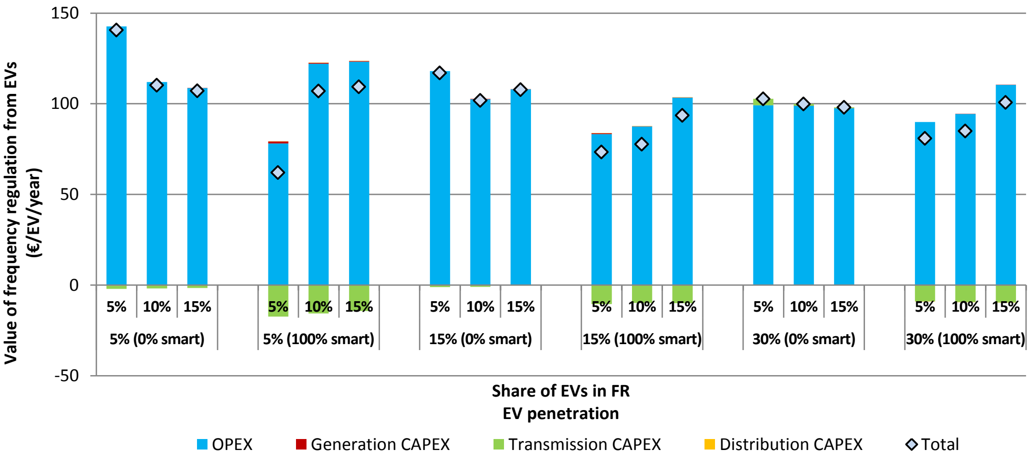


Figure 3.20 Cost savings from FR provision by EVs in the UK and Ireland in 2030

The values of FR per single EV are not too dissimilar to what has been observed for other systems. In cases with 0% smart scheduling the value of FR provision is observed to vary in the following ranges: €107-141 for Low, €102-117 for Medium and €98-103/EV/year for High EV penetration. When all vehicles participate in smart scheduling, the values observed are €62-109 for Low, €73-94 for Medium and €81-101/EV/year for High EV penetration.

3.4 Environmental impact of additional electricity demand driven by EVs

Given that EVs are increasingly seen as one of the key instruments to enable decarbonisation of transport energy demand, it is of particular interest to investigate the impact of EV demand on the environmental performance of European power systems. As stated before, two key quantities will be presented in this section: impact of electromobility on carbon emissions from the electricity sector and the implications of adding EV demand on the ability of the system to integrate intermittent renewable sources.

3.4.1 System integration of renewables

One of the benefits of flexible EV charging, potentially reflected in both cost and carbon savings, is the ability to adjust the charging patterns to maximise the absorption of intermittent renewable output (primarily wind and PV). This is particularly relevant in the context of decarbonising future European electricity systems, which is expected to be delivered by deploying significant volumes of intermittent renewable generation capacity.

As part of our analysis presented in this report, we also quantify the impact of EV deployment at various penetration levels as well as various levels of their flexibility on the ability of the power systems to integrate intermittent renewables. The key parameter to establish this ability is the level of necessary renewable curtailment, which may be inevitable during periods of high renewable output and low demand, combined with the delivery of energy from conventional generators as a by-product of their provision of ancillary services.

In this section we present the assessment of curtailment levels for three key intermittent renewable technologies: (i) wind, (ii) PV and (iii) CSP[14]. Unlike the cost and carbon implications, the curtailment levels reported in this section refer only to the observed system

[14] Curtailed CSP output reported in this section also includes thermal storage losses.

(presenting the curtailment implications for the entire European system would dilute the effects and make it difficult to visualise the impact of smart EV charging).

Figure 3.21 presents the wind curtailment levels in the four systems for varying penetrations of EVs and smart scheduling. Wind curtailment (and the curtailment of other intermittent renewable generation technologies) is presented as percentage relative to total annually available energy from this source. There is an obvious reduction in wind curtailment levels with the introduction of smart charging, and this effect becomes more visible at higher EV penetrations. The curtailment reduction effect in the DE-DK system is less pronounced due to the low curtailment level in the baseline case (without EVs). With 100% of smart charging at High EV penetration (30%) we find that, compared to the baseline case, the wind curtailment drops by 17% in Spain, 26% in UK-RI, 32% in DE-DK and 52% in Italy.

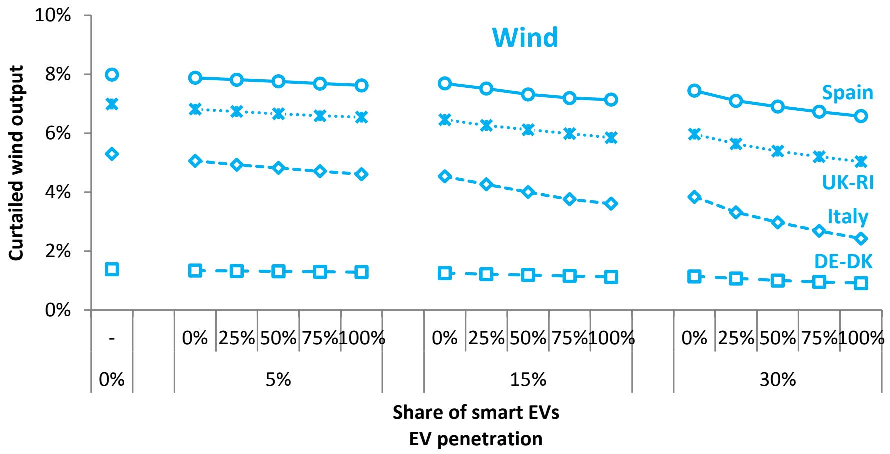


Figure 3.21 Annual wind output curtailment in four systems in 2030

The PV relative curtailment levels are presented in Figure 3.22 and are generally characterised by considerably lower percentages than wind curtailment. Even in the baseline case, the highest PV curtailment (observed in Spain) is around 0.6%. In the DE-DK system no PV curtailment is observed in any of the analysed cases. As for the other systems, the greatest reduction in curtailment at High penetration and 100% smart scheduling is seen in Spain (78%) and Italy (56%), while in the UK-RI system there is virtually no change in PV curtailment level. The latter observation can be explained by the fact that the installed PV capacity in the UK-RI system is almost 20 times lower than wind, and therefore the decisions on when to charge EVs are much more guided by the opportunities to save wind.

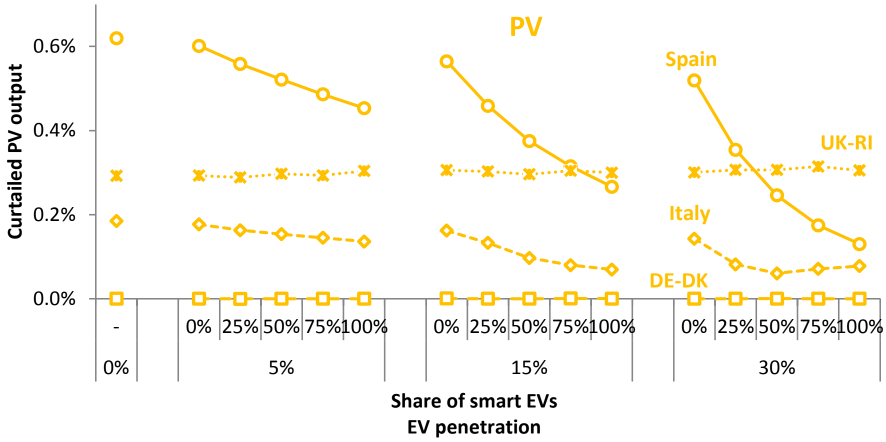


Figure 3.22 Annual PV output curtailment in four systems in 2030

CSP capacity is assumed to exist only in the Spanish and Italian system in 2030, and this is why only these two systems are included in Figure 3.23. There seems to be no major impact of EV deployment and smart charging on the curtailed CSP output (which as explained before also contain the thermal losses). Given that the CSP output is more controllable than PV due to the existence of thermal energy storage that allows its output to be concentrated during system peak hours, there is no great impact of EV flexibility on the curtailed level of this renewable technology.

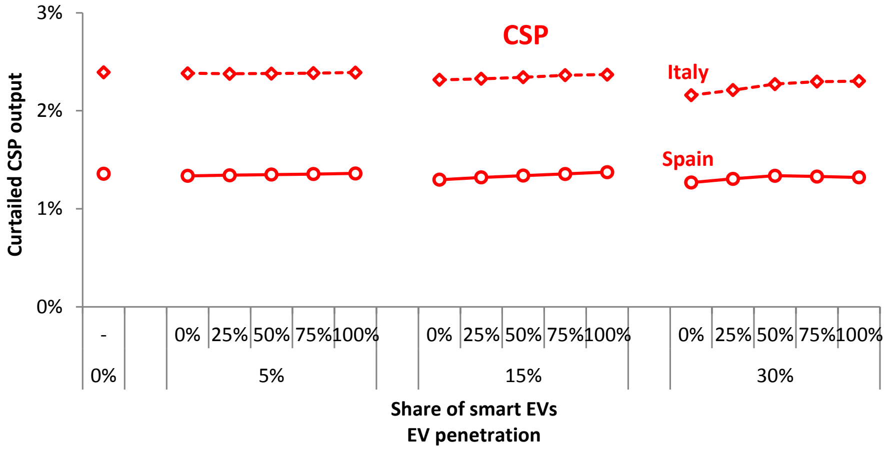


Figure 3.23 Annual CSP output curtailment in four systems in 2030

Finally, Figure 3.24 presents the total curtailment level for all three renewable technologies. For the UK-RI system the total curtailment is obviously dominated by wind, whereas for other systems it results from a combined effect of curtailment levels observed for the three RES generation technologies. The highest relative reduction in RES curtailment is observed for Italy (44% at High penetration, 100% smart point), followed by DE-DK (31%), UK-RI (26%) and Spain (20%).

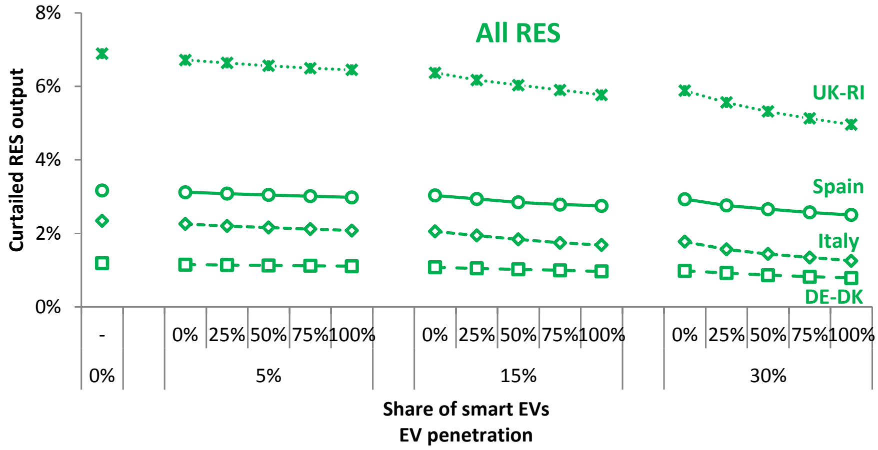


Figure 3.24 Annual curtailment of all intermittent RES in four systems in 2030

On the other hand, when absolute volumes of curtailed renewable energy are observed for the same case, the highest reduction in curtailment by far is seen in the UK-RI system (5.1 TWh), followed by Italy (1.4 TWh), Spain (1.0 TWh) and DE-DK (0.8 TWh). The absolute level of RES output curtailment broken down into technologies for all four systems is shown in Figure 3.25, which compares the cases without EVs and with High (30%) EV penetration and fully smart EV control. The figure confirms that the dominant component in RES curtailment in all four systems is wind generation.

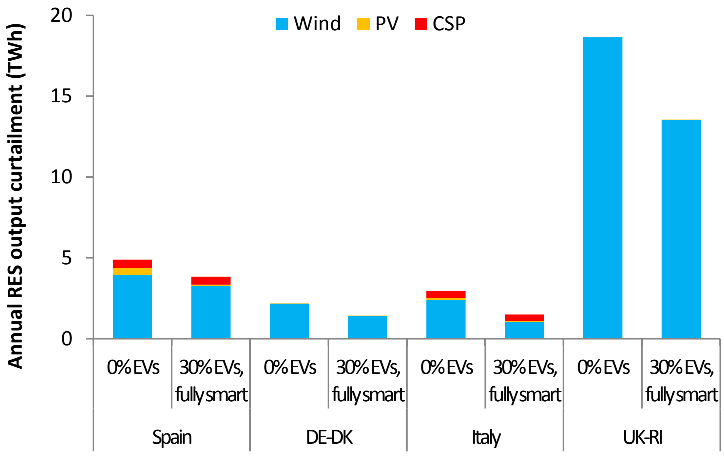


Figure 3.25 Curtailed output RES in four systems in 2030

3.4.2 CO_2 emissions

As demonstrated in Section 3.3, the additional electricity demand for EV charging generally increases the investment and operation cost of a system where it is being added. The magnitude of this increase however will depend not only on the volume of additional EV demand, but also on whether and to which extent this demand is managed. To that end, the previous sections have shown that the cost of integrating EV demand may be reduced several times if smart charging schemes are adopted and EVs act as FR providers.

The impact of EV demand on carbon emissions from the electricity system will be governed by similar mechanisms as cost savings. In other words, the incremental demand from EVs is most likely to increase system emissions, while smart charging would be expected to mitigate this increase in CO_2 emissions. However, given that a cheaper generation technology does not necessarily have to be the one with a lower emission factor (although the cost of emissions has been factored into our analysis through the carbon price), the impact on carbon emissions will be driven by the composition of the generation portfolio in a given system and the cost and emission parameters of each technology. That being said, the marginal cost of low-carbon generation technologies (in particular wind, solar and nuclear) is generally much lower than the cost of thermal generation technologies. One might therefore expect that in a cost-optimal solution, where the capacities of low-carbon technologies are fixed, the system would minimise its cost by maximising the utilisation of zero to low marginal cost plants at the expense of conventional thermal generation, and that would also imply lower emission levels.

Increase in total system carbon emissions

In a similar approach to reporting cost savings in the previous section, the carbon emission increases or decreases presented in this section will refer to the entire interconnected European system, while the assumption is that EVs are deployed only in one of the observed systems at the time.

The summary of additional carbon emissions quantified in our case studies for the four European systems is provided in Figure 3.26. The results are shown for all three penetration levels (Low, Medium, High) and for the share of smart EV scheduling varying between 0% and 100% in 25% steps. For the sake of readability, the emissions for the Low case are also shown in an inset with an adjusted scale in the top left corner of the chart.

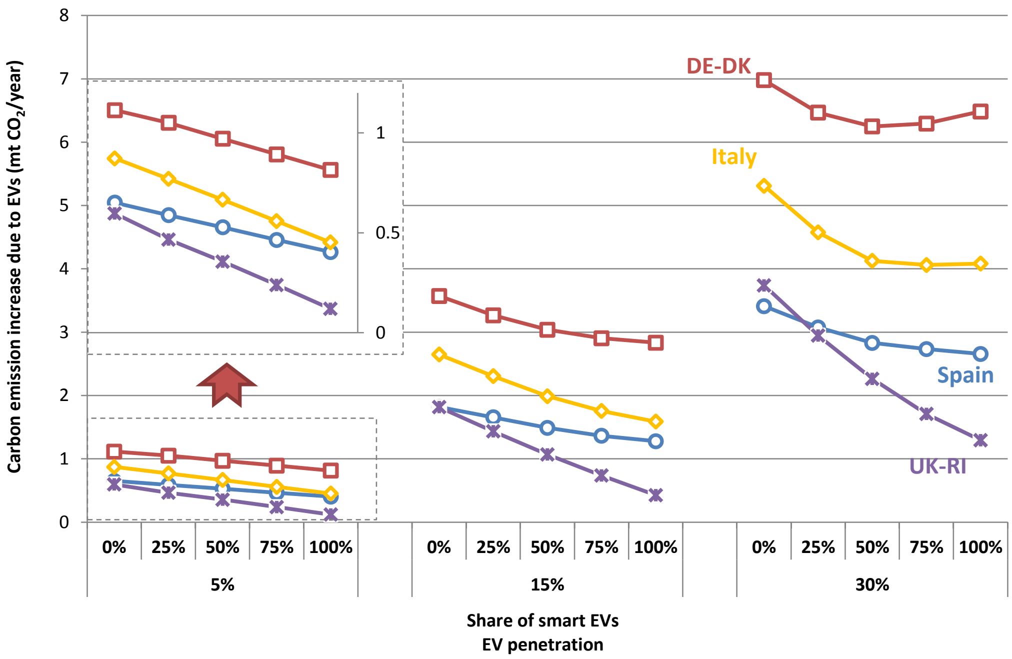


Figure 3.26 Additional annual carbon emissions due to EV deployment in 2030

Carbon emissions per EV

When observing the 0% smart cases in Figure 3.26, it is not surprising that the magnitude of incremental emissions broadly follows the number of cars assumed in different systems – the largest size of vehicle fleet is assumed for the German-Danish system (DE-DK), followed by Italy, UK-Irish system (UK-RI) and Spain. In order to provide a more comparable quantity across different systems, Figure 3.27 expresses the emission increase observed in different systems per EV.

At 0% smart penetration the carbon footprint of supplying electricity to a single EV depends on the carbon intensity of a given system. We note that this varies between about 300 kg for the UK-RI system, and about 400-500 kg CO_2 per annum for the other three systems. The rate of decrease of emissions per EV as the smart scheduling uptake begins to grow is the function of the penetration rate, but even more so of how flexible EV charging is used to minimise cost in a given system. In the UK-RI and Spanish systems, the key source of value of smart charging are OPEX savings from reduced renewable output curtailment, and to a lesser extent a more efficient operation (i.e. high load factors) of CCGT units.[15]

In the Italian and DE-DK system on the other hand, RES curtailment seems to be much less of an issue (see Section 3.4.1), while on the other hand these systems feature a considerable amount of conventional coal plants. This is why at high EV penetrations and high smart scheduling shares we observe that the emission reduction trend tails off or even reverses. This is a consequence of a very fine interaction between the provision of reserve and FR services by conventional (coal and CCGT) units. As the aggregate demand profile is made flatter by smart EV scheduling, it becomes gradually more favourable to use coal plants to provide spinning reserve given that according to the cost assumptions they have a lower operating cost at minimum output level (which is where the maximum spinning reserve contribution can be provided). Also, with a flatter demand profile, there is less need for costly start-ups and shut-downs of these units, which slightly tilts the balance in favour of using coal instead of CCGT units to provide spinning reserve, with the consequence of higher coal generation output and hence slightly higher carbon emissions.

[15] In the case of UK-RI system an additional challenge for efficient renewable integration is represented by limited interconnection possibilities of these island systems.

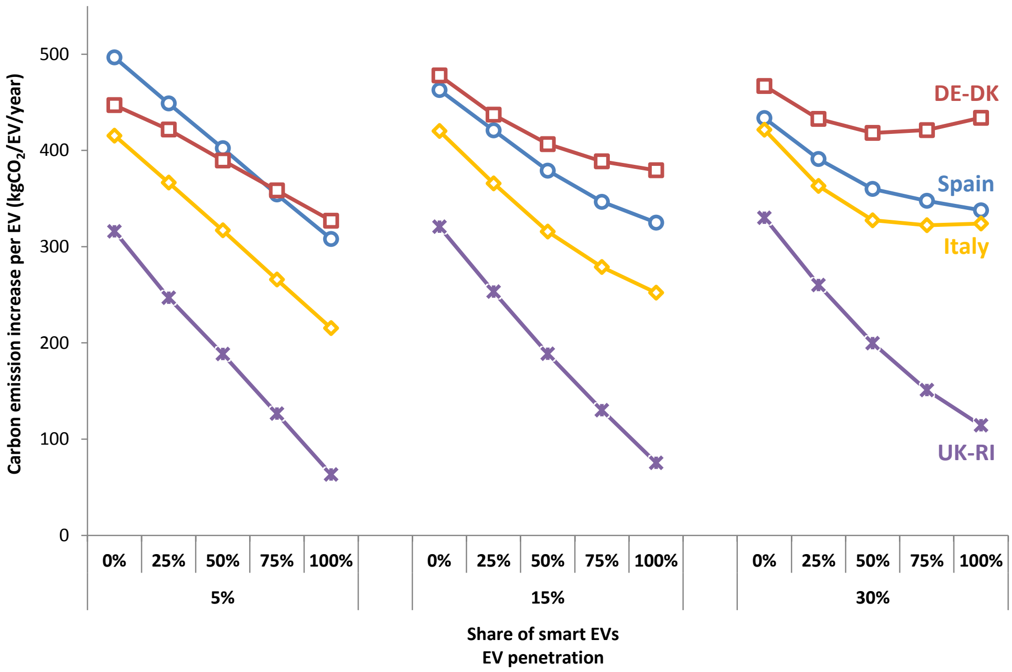


Figure 3.27 Additional annual carbon emissions per EV

Impact of FR provision by EVs on carbon emissions

Section 3.3 explored the economic impacts of EVs being able to provide FR to the system operator, revealing significant potential cost savings. In order to study the impact of FR provision by EVs on carbon emissions, we quantify in Figure 3.28 the incremental emissions from power generation for cases where EVs act as ancillary service providers. An immediate observation is that, similar to smart EV scheduling, FR provision also reduces carbon emissions. The emission reduction is broadly proportional to the increasing share of EVs participating in FR provision. Unlike with smart scheduling, no tailing off effect is observed.

Carbon savings with EVs providing FR are the consequence of more efficient operation of conventional thermal generation, i.e. less requirement for these generators to run part-loaded at lower efficiency and with higher emissions. The slope of emission decline in different systems is determined by the type of generation technology that is being displaced from FR provision by EVs. In the case of DE-DK and Italian systems, the marginal FR providers displaced by EVs seem to be conventional coal units. Given that EVs reduce the need to run part-loaded coal units, this reduces their output characterised by a relatively high emission factor; hence the rate of emission decline is faster. In the Spanish system on the other hand, it is the CCGT units that provide most of FR, and the displaced CCGT output has a lower impact and drives a slower decline of carbon emissions with increasing share of EVs providing FR. Another factor contributing to a slower decline in emissions for Spain is the lower ratio between the number of vehicles and the level of FR requirement in the system, which implies that a higher percentage of EV fleet would be needed to displace one MW of FR from conventional generators and generate the corresponding emission savings.

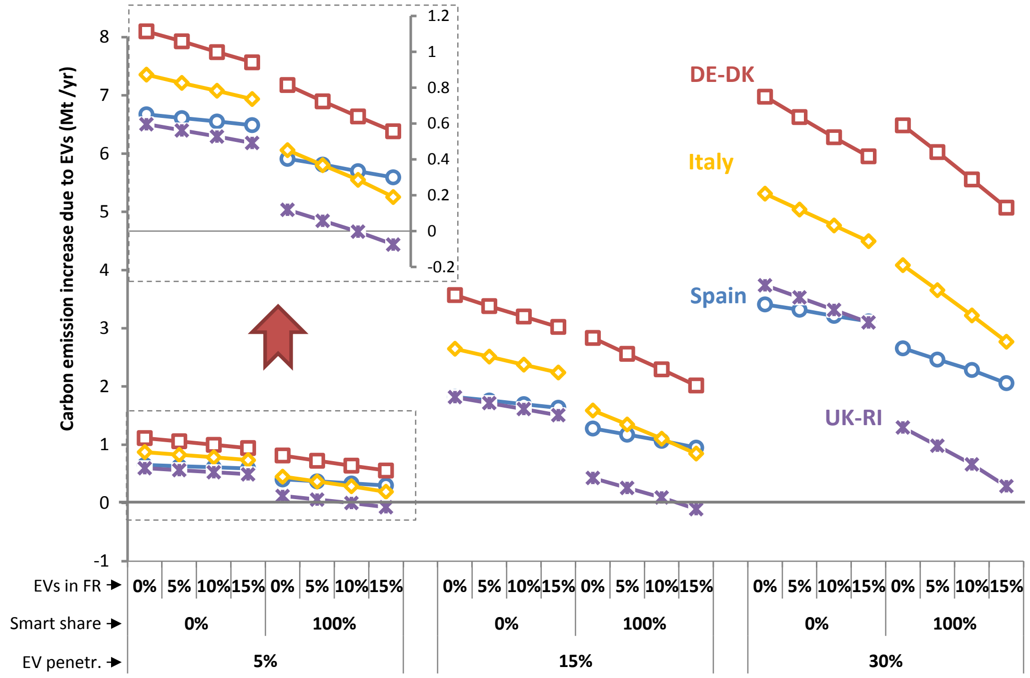


Figure 3.28 Additional annual carbon emissions with EVs contributing to frequency regulation

In the UK-RI system, despite a relatively low car to FR requirement ratio and FR being provided predominantly by CCGT units, the decline in emissions is relatively steep. A specific feature of the UK-RI system is that it has the highest share of wind and therefore requires comparably the highest volume of reserve capacity in the system. Given that the spinning reserve and FR are provided by the same (mostly CCGT) units, relaxing the FR requirements driven by FR provision by EVs also enables that the spinning reserve is provided more efficiently, i.e. with lower part-loading losses and resulting savings in operating cost and carbon emissions. For the same reason, it is also interesting to note that in the UK-RI system the combination of fully smart charging (100%) and 15% of EVs contributing to FR provision may result in negative emission increment (at Low and Medium penetrations) i.e. in reduced carbon emissions from the power system despite the introduction of additional EV demand. This will obviously make the electrification of road transport an additionally attractive proposition from the aspect of energy system decarbonisation.

Figure 3.29 quantifies the carbon impact of additional EV demand i.e. incremental emissions from electricity sector per EV for various cases of FR provision. As already noted, the combination of smart EV scheduling and FR provision yields the highest carbon reduction. In the case of the UK-RI system flexible EVs are even capable of completely offsetting the carbon increase, so that the CO_2 emissions from the electricity sector actually diminish as the result of deploying smart-controlled EVs (at Low and Medium penetrations).

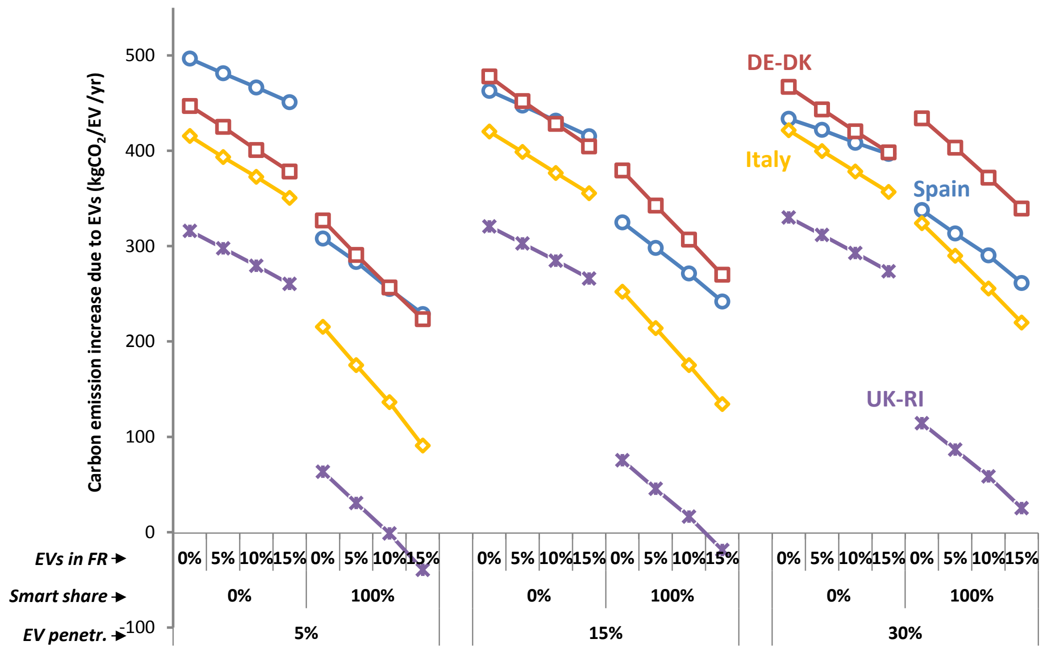


Figure 3.29 Additional annual carbon emissions per EV with FR provision

Comparison with carbon emission offsets in road transport

We further put the additional emissions associated with electricity demand for charging EVs into the context of emissions avoided through the electrification of road transport in Europe. To that end, an assumption needs to be made with respect to the carbon emission factor (in gCO_2/km) of conventional passenger vehicles that are being replaced by EVs in the 2030 time horizon. It is therefore relevant to refer to the most recent emission performance data on one hand, while also considering the future emission limits defined at the EU level that car manufacturers will have to comply with in the future.

According to [31], the carbon emissions of new conventional passenger cars in the European Union in 2013 were 127 gCO_2/km, which continued the decline in emission factors compared to the values observed in 2000 (172 gCO_2/km), 2005 (162 gCO_2/km) and 2010 (140 gCO_2/km). Key drivers behind these improvements were the increased share of diesel vehicles in the fleet (from 31% in 2000 to 52% in 2013) and the improvements in fuel efficiency, which more than offset the slight increase in average vehicle mass observed over the last decade (from 1.35 t in 2004 to 1.39 t in 2013).

As part of its long-term climate change policy, European Union has defined mandatory emission reduction targets for new passenger cars in the 2015-2020 horizon [32]. The fleet average to be achieved by all new cars is 130 g/km by 2015 (with the target gradually phased in from 2012) and 95 g/km by 2021 (phased in from 2020).[16] The 2015 and 2021 targets represent reductions of 18% and 40% respectively compared with the 2007 fleet average of 159 g/km. The fleet average limits apply for each (major) manufacturer, which

[16] According to European Environmental Agency data [31] the 2015 target (130 g/km) has already been exceeded in 2013 (127 g/km).

means that heavier cars are allowed higher emissions than lighter cars while preserving the overall fleet average.

It is understood that any carbon emission improvements beyond 2020, which have not been mandated yet but are being considered, will require a full hybridisation of manufacturer vehicle fleets in order to reach the target, either through hybrid or plug-in hybrid vehicles, or through including pure battery EVs in the fleet. The 2021 target (95 g/km) translates into the fuel consumption of approximately 4.1 litres of petrol per 100 km or 3.6 litres of diesel per 100 km, and reduction beyond those levels appears unlikely for conventional, purely ICE-based vehicles. The implication for the evaluation of carbon emissions displaced by EVs in the 2030 horizon is that the average end-of-pipe emissions in 2030 will be based on a mix of fuel and electricity-driven vehicles, whereas an adequate assessment of avoided emissions would require the comparison only with those vehicles not relying on grid-supplied electricity to power their journeys. In addition, the CO_2 emissions from passenger vehicles in 2030 will be a result of a mix of both new and used vehicles. It is therefore considered appropriate to assume the 2021 emission target of 95 g/km will be applicable to the non-electrified share of passenger vehicles in 2030 and to use this value to estimate the net effect of EVs on carbon emission.

Based on this approach, the net effect of EV deployment in the four observed systems after deducting the emission offset from road transport is depicted in Figure 3.30. Change in emissions resulting from EV deployment is presented per EV for each of the three EV penetrations (Low, Medium and High) and each of the following three cases: (i) BaU (no smart charging), (ii) smart scheduling with 100% of EVs participating, and (iii) fully smart charging with 100% smart scheduling and 15% FR provision. Emission increases per EV before accounting for offsets in road transport (corresponding to the values presented in Figure 3.29) are also shown for reference, with dashed lines.

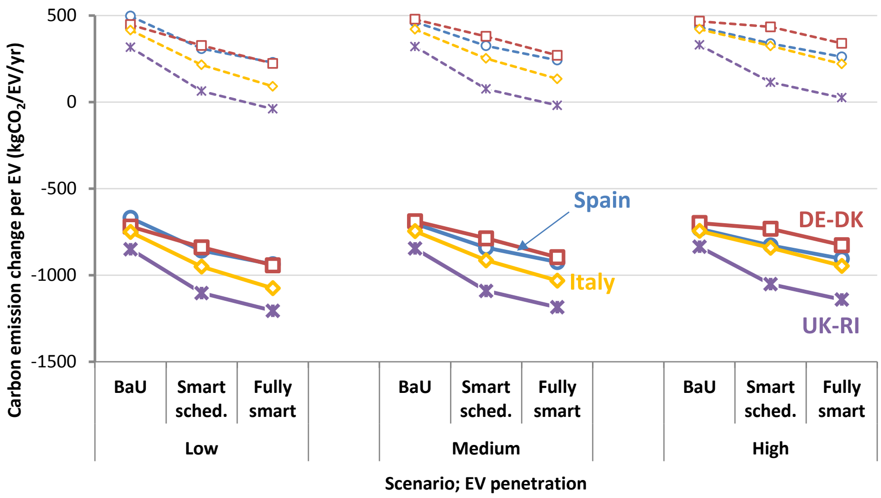


Figure 3.30 Net additional annual carbon emissions per EV when accounting for emission offsets in road transport

Given that the electricity supply in 2030 is assumed to be based predominantly on low- or zero-carbon technologies, the net effect of EV deployment on carbon emissions is clearly positive i.e. the aggregate emissions from vehicle use reduce for all penetration levels and cases studied in this analysis. This follows directly from the assumed carbon emission factor for displaced fossil-fuel road transport of 95 g/km, which result in annual emissions per vehicle of 1,166 $kgCO_2$.[17] Due to the low carbon intensity of the assumed 2030 electricity generation technology mix for the four systems, this value far exceeds the incremental carbon emissions driven by increased EV demand, resulting in overall carbon benefits for the society.

Finally, when discussing the carbon performance assessment of electricity systems featuring large numbers of EVs, it has to be noted that the analysis presented in this report only focuses on the emissions associated with end-of-pipe emissions i.e. the usage phase of EVs. The carbon impact assessment does not take into account the emissions associated with the manufacturing and dismantling phases of the EV life cycle, and how these compare to corresponding phases in the life of conventional vehicles. This sort of appraisal requires a life-cycle assessment (LCA) approach, which is out of scope of this report, but is studied in detail in Deliverable 9.5 of Green eMotion.[18]

3.5 Discussion

This section summarises the cross-system findings of our economic valuation studies for smart EV charging. For that purpose, Table 3.1 provides an overview of incremental cost to supply EV demand (expressed per EV) when no smart charging takes place, as well as the incremental costs for cases with 100% smart scheduling and fully smart EV control (100% smart scheduling combined with FR provision by 15% of EVs). Note that the incremental cost per EV presented in Table 3.1 has been found by dividing the additional system cost with the total number of EVs in the system, and not only those participating in smart EV control (hence the differences in numbers between this table and considerations of value per EV in Table 3.2).

[17] As stated in Appendix 1 (page 85), the average annual distance driven per EV has been assumed at 12,300 km based on [13] and [14].

[18] Deliverable 9.5 ("Environmental impacts of widespread shifting towards electricity based mobility") is expected to become available on the Green eMotion website in early 2015: http://www.greenemotion-project.eu/dissemination/deliverables-evaluations-demonstrations.php.

Table 3.1 Incremental costs per EV in four systems

	Spain	**DE-DK**	**Italy**	**UK-RI**
Average incremental cost per EV – non-smart [€/EV/year]				
Low	186	203	203	182
Medium	191	216	209	191
High	195	223	219	200
Average incremental cost per EV – 100% smart scheduling [€/EV/year]				
Low	60	113	55	82
Medium	78	136	86	89
High	104	146	110	96
Average incremental cost per EV – fully smart [€/EV/year]				
Low	40	97	32	66
Medium	57	118	66	75
High	89	134	94	81
Proportion of incremental cost avoided through fully smart control				
Low	79%	52%	84%	64%
Medium	74%	45%	69%	61%
High	70%	40%	57%	59%

We note that the cost of supplying additional EV demand in the business-as-usual approach varies around €200/EV/year, with the extremes lying about 10% below and above this value. Also, this value slightly increases with higher EV penetrations. As elaborated in Section 3.3, the bulk of the incremental cost is driven by the increase in operating cost, although there are also considerable increases in distribution and generation CAPEX.

The value of smart charging in terms of the avoided incremental cost of EV integration represents a significant proportion of the baseline incremental cost. In all four systems the value of smart charging (i.e. the proportion of additional cost avoided through smart charging) is the function of system properties, and slowly reduces with increasing EV penetrations. The cost offset varies from 57-84% for Italy, 70-79% for Spain and 59-64% for UK-RI to 40-52% for the DE-DK system. It is evident that in all of these cases the cost savings from smart charging represent a significant proportion of the system integration cost of EVs that cannot be ignored as part of a cost-efficient EV deployment strategy.

Another common finding from the system studies is that the value of FR provision by EVs brings cost benefits on a similar scale to smart scheduling, as illustrated in the first two parts of Table 3.2. Both the value of smart scheduling and FR provision has been determined as in Section 3.3, i.e. by dividing the cost savings with the number of EVs participating in smart control strategies. The value of FR provision without any smart scheduling varies between €50 and €120/EV/year across different system and penetrations, with the highest values observed at Low EV penetrations.

Table 3.2 Values of smart charging and FR provision per EV in four systems

	Spain	DE-DK	Italy	UK-RI
Value of smart charging per EV for 100% smart scheduling (no FR) [€/EV/year]				
Low	126	90	148	100
Medium	113	80	122	102
High	91	77	108	104
Average value of FR provision by EVs across all studies (no smart scheduling) [€/EV/year]				
Low	67	65	89	119
Medium	69	66	77	109
High	55	50	77	100
Average value of simultaneous 100% smart charging and FR provision [€/EV/year]				
Low	265	196	309	193
Medium	258	196	256	183
High	193	159	203	193
Synergistic value multiplier				
Low	1.38	1.26	1.30	0.88
Medium	1.42	1.33	1.28	0.87
High	1.32	1.25	1.09	0.94
Proportion of incremental cost avoided through combined services				
Low	142.9%	96.7%	152.1%	105.7%
Medium	135.2%	90.5%	122.5%	95.9%
High	99.1%	71.1%	92.7%	96.3%
Capitalised value of combined smart charging and FR provision [€/EV]				
Low	1,821	1,347	2,118	1,323
Medium	1,770	1,342	1,755	1,258
High	1,327	1,089	1,391	1,324

When smart EV demand shifting and FR provision are both simultaneously present in the system, we observe in all systems except UK-RI that the combined value of the two services is greater than the sum of two services provided separately (third part of Table 3.2).[19] This suggests that in the Spanish, Italian and DE-DK systems there are synergies when the same EV fleet provides both services (smart scheduling and FR provision) at the same time. This is further quantified in the fourth part of the table, where the synergistic value multiplier is calculated for all systems as the ratio between the value of combined provision of both services and the sum of the values of two services provided individually. For all systems except UK-RI this ratio is higher than 1, suggesting a positive mutual impact between smart scheduling and providing FR.

In the UK-RI system on the other hand there seems to be a mild conflict between the simultaneous provision of both services, as the synergistic value multiplier takes values below 1 (although it approaches 1 as the EV penetration grows). The reason for this is understood to lie in combination of high relative share of wind capacity in the UK-RI system and its geographical location that is inherently more limited in terms of interconnection capacity towards the neighbouring systems. When smart scheduling is present, it tries to

[19] The value found in our case studies is broadly consistent with the value of €227/EV/year reported in [5].

adjust its demand profile to fluctuations in wind output, which requires considerable variations in controlled EV demand. This on the other hand results in reduced FR provision capability during low-wind and low-demand periods, so that frequency regulation in these conditions needs to be sourced from conventional generation. Nevertheless, the magnitude of this conflicting effect in the UK-RI system is not very high.

It is quite interesting to compare the combined value of smart scheduling and FR provision per vehicle that participates in both aspects of smart EV control with the incremental cost of supplying EV demand in 0% smart case. This is provided in the part of Table 3.2 titled "Proportion of incremental cost avoided through combined services". It suggests that in all systems a great majority of incremental cost can be offset through smart EV control. In some cases the value even exceeds the business-as-usual incremental cost per EV by more than 50%. Nevertheless, it has to be noted that negative incremental cost would only be valid for the proportion of vehicles participating in both smart charging and FR provision, and that share is never assumed to be higher than 15% in our studies. This is why the aggregate incremental cost seen for the entire fleet is still positive despite both smart charging and FR provision being active, as depicted in e.g. Figure 3.2 or Figure 3.7 or in Table 3.1.

Finally, in order to provide an estimate of the capitalised value of annual cost savings quantified in this section, the last part of Table 3.2 ("Capitalised value of combined smart charging and FR provision") converts the annualised cost savings for cases with combined smart charging and FR provision into upfront capital values. This is carried out by assuming an interest rate of 7.5% and an equipment lifetime of 10 years, which results in a capitalisation factor of 6.86.[20] The capitalised values obtained from the studies are rather significant, ranging between about €1,100 to €2,100 per EV, depending on the system and EV penetration. These values are non-negligible when compared with the upfront EV purchase cost, suggesting that EV ownership could be made more affordable if a mechanism is devised to reward flexible EV owners for the value they provide to the system.

The analysis of environmental impacts of EV deployment presented in Section 3.4 has further shown that EV deployment in general, and smart EV control in particular may result in significant reductions in carbon emissions from the electricity system. The net emission reduction effect of EV deployment in the assumed 2030 scenario when the emission reductions in road transport are taken into consideration is even more pronounced. At the same time, flexible EV management approaches also have the potential to deliver considerable reductions in curtailment of intermittent renewable output.

[20] Using this approach, the annualised cost savings of €100/EV/year would result in a capitalised value of €686/EV.

4 Conclusions and further analysis

4.1 Key findings

The whole-system assessment of the economic and environmental impact of EVs presented in this report quantifies the cost and emission implications of integrating electrified road transport into European power systems.

4.1.1 Economic impact of EV rollout

The incremental cost of supplying EV demand is found to be a function of the control strategies implemented with newly rolled out EVs. In the business-as-usual (BaU) approach, where no smart charging or ancillary service provision from EVs takes place, the incremental annualised cost of electricity supply per EV for EV penetration levels between 5% and 30% is relatively robust around €200/EV/year in all four analysed systems (it broadly varies within ±10% of this value, with higher values generally associated with higher EV penetrations and vice versa). Our modelling quantified different components of this cost, where the dominant constituent is the operating cost increase, followed by increases in distribution and generation CAPEX, and to a much lesser extent by additional transmission CAPEX. OPEX increases are required to supply the additional demand, while CAPEX cost categories increase due to the need to meet the disproportionately high increase in peak demand driven by BaU EV deployment.

We further investigated the value of smart EV demand scheduling, i.e. the opportunity for the system to coordinate EV demand in order to deliver the required energy without compromising the users' ability to make their journeys, but also to schedule the delivery of this energy with the aim to optimise the cost performance of the system. The value of smart charging for the system in terms of annualised cost savings is found to be significant, ranging between €92 and €156/EV/year across different systems, EV penetrations and smart participation rates. These values represent between 41% and 77% of incremental BaU cost per EV when no smart charging takes place. When studying the composition of these values, we find that the largest contribution to this value was made by OPEX savings, although their share was found to diminish with increasing EV penetrations and smart participation rates. At the same time distribution CAPEX savings, which represent the second largest cost savings category, gain in magnitude as the penetrations of EVs and smart charging increase. The third major component of value of smart charging is generation CAPEX savings. Savings in both CAPEX categories result from reduced peak demand with smart EV demand scheduling, while OPEX savings arise from improved load factors of low marginal-cost generators and reduced renewable curtailment.

We have performed further system simulations in order to estimate the value of EVs providing frequency regulation, and this value is found to be comparable to the value of smart EV scheduling. Savings generated by FR provision are almost exclusively made up of OPEX savings, driven by displacing inefficient part-loaded conventional generation as FR providers. There is also a simultaneous emission reduction effect from EVs providing FR.

In three out of four simulated systems we note that when an EV participates both in smart charging and in FR provision, the resulting economic value per EV is higher than the sum of the values of providing each service separately. This suggests there are synergistic effects when EVs participate in both services that tend to be stronger than conflicts between the two services.

In all four systems the value of smart EV control (i.e. the proportion of additional cost avoided through smart scheduling and FR provision by EVs) is the function of system properties, and slowly reduces with increasing EV penetrations. The system-level cost offset varies from 57-84% for Italy, 70-79% for Spain and 59-64% for UK-RI to 40-52% for the DE-DK system. It is evident that in all of these cases the cost savings from smart charging represent a significant proportion of the system integration cost of EVs that cannot be ignored as part of a cost-efficient EV deployment strategy. The integration cost per EV for cases with no smart control (BaU), 100% smart scheduling and fully smart control (100% smart scheduling and FR provision) are presented in Figure 4.1, where the cost is also disaggregated across different segments of the electricity system.

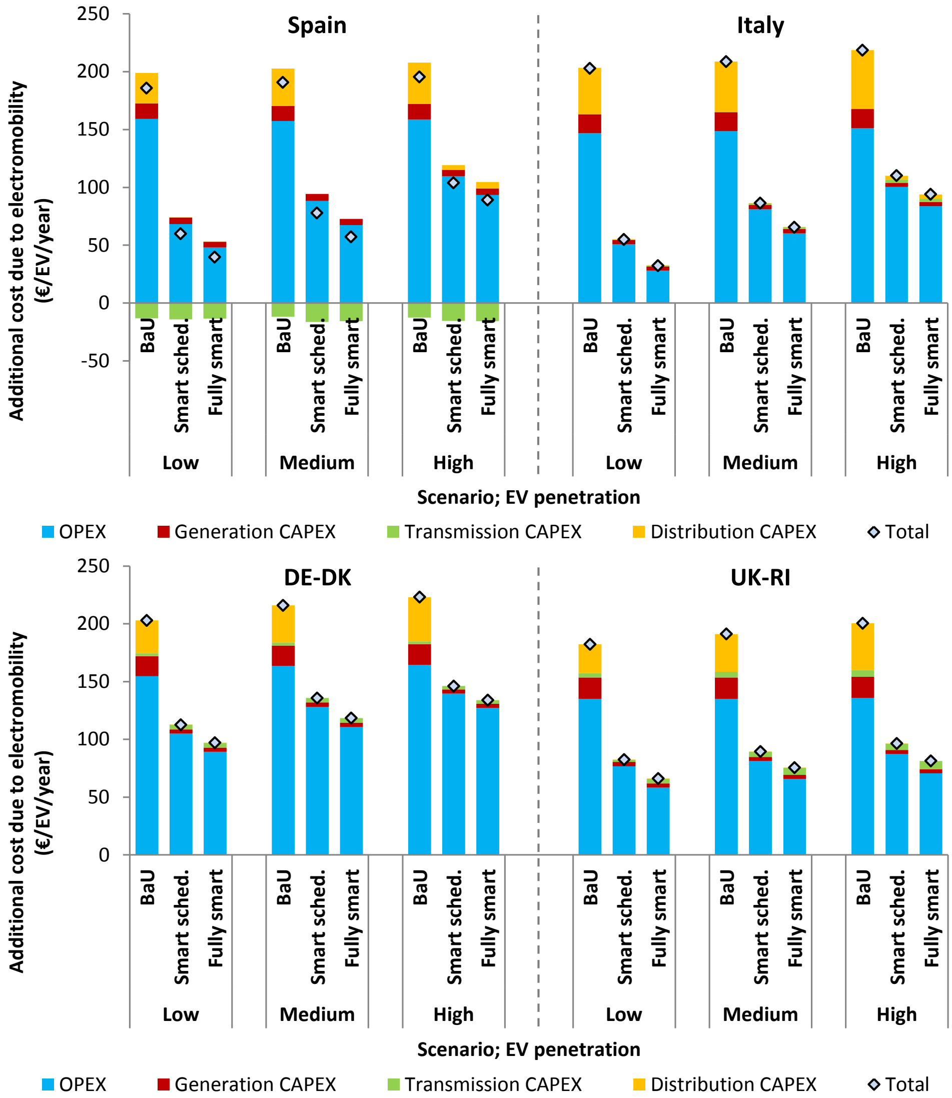


Figure 4.1 Summary of incremental cost of EV integration (per EV) in four systems

As part of the climate change policy, promoting EV deployment is compatible with the continued expansion of renewable and other low-carbon generation technologies. High RES penetration assumed in our studies is therefore in line with the long-term EU carbon emission targets. Our previous work suggests that the impact of EVs and the corresponding value of smart EV charging would reduce by broadly 50% in systems with low RES penetrations, mostly due to the decrease in OPEX savings.

4.1.2 Environmental implications of EV deployment

The analysis of CO_2 emissions associated with EV deployment has further shown that smart charging and FR provision from EVs may result in significant reductions in carbon emissions from the electricity system, although these reductions were found to depend greatly on the system in question. At 0% smart penetration the carbon footprint of supplying electricity to a single EV varies between about 300 and 500 kg CO_2 per annum. Increasing the uptake of smart charging generally reduces emissions per EV, at a rate that is a function of system characteristics. Reduction in carbon emissions through smart EV control is driven by improved load factors of low-carbon generation, reduced renewable curtailment, and improved efficiency due to less part-loaded operation of conventional generators providing FR. The incremental carbon emissions per EV for BaU, 100% smart scheduling and fully smart control are shown in Figure 4.2.

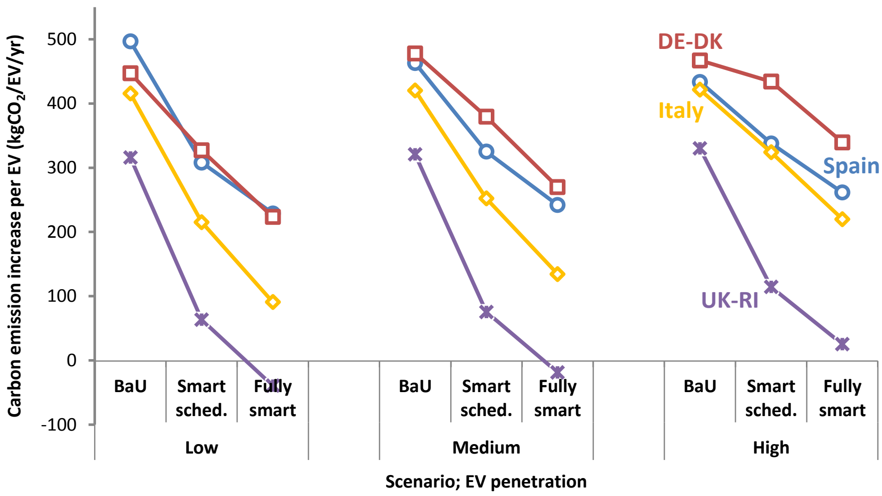


Figure 4.2 Summary of incremental carbon emissions associated with EV deployment (per EV) in four systems

The net emission reduction effect of EV deployment in the assumed 2030 scenario when the emission reductions in road transport are taken into consideration is distinctly positive when observed in a wider energy system. At the same time, flexible EV management approaches also have the potential to deliver considerable reductions in curtailment of intermittent renewable output such as solar and wind.

4.1.3 Challenges for development of market and regulatory framework

Our analysis has demonstrated the existence of significant economic opportunities for flexible EV charging, that can substantially reduce the system integration cost of EV deployment. In other words, smart integration of EVs into electricity system operation and design will not undermine their rollout, as the additional cost involved is expected to be modest. Nevertheless, it has to be noted that the cost savings quantified in our case studies represent a fundamental economic value of flexible EV management; our analysis does not suggest how this economic value would materialise in a given market and regulatory environment. Implementation of commercial arrangements capable of rewarding flexible providers for the value they provide to the system is another challenge that will need to be addressed to support an efficient Europe-wide EV rollout, and this challenge will be addressed in later GeM Deliverables 9.6 (“Barriers, gaps, and commercial and regulatory framework for broad rollout of electromobility”) and 9.7 (“Policy evolution recommendations and stakeholder actions towards effective integration of EV in EU”).

As shown in the analysis, the benefits provided by flexible EV demand span multiple sectors of the electricity system – balancing and energy arbitrage, ancillary service provision, generation capacity adequacy, and transmission and distribution networks. These sectors are generally characterised by different market structures, competition levels and regulation, which makes it challenging to deliver adequate revenues to flexible EV owners from such diverse sources. Potentially high benefits of finding an appropriate framework to include EVs in all aspects of power system planning and operation justify the effort to find innovative solutions that will allow flexible EV users to be adequately rewarded for their contribution to efficient management of electricity systems.

4.2 Relevance for life-cycle environmental impact analysis of EVs

Results of the whole-system impact analysis of EV deployment presented in the report have direct implications for the environmental LCA that is the subject of Deliverable 9.5 of Green eMotion. One of the outputs of the analytical model used in this study are carbon emissions from the electricity system for various scenarios with respect to EV deployment and participation in smart charging schemes. These represent an input for the assessment of the usage phase of an EV life cycle (the other two phases covered by environmental LCA in D9.5 include the manufacturing and dismantling).

The outputs of the analysis presented in this report will therefore be used to inform the environmental impact analysis of electromobility, so that the LCA can be conducted not only based on current level of grid emissions, but also taking into account the expected emissions in the future, while considering different approaches to EV charge scheduling and contribution to ancillary service provision.

4.3 Relevance for barrier and gap analysis

As already discussed, smart charging of EVs has the potential to significantly reduce the cost of EV integration, however those cost savings are split across multiple sectors of the electricity system (generation, transmission, distribution, operation). The fact that these sectors have markedly different commercial arrangements (some are liberalised, while the others are regulated) represents a potential barrier for the value of smart charging to materialise using the present commercial and regulatory framework.

Barriers and gaps to large-scale EV deployment in Europe are assessed in detail in Deliverable 9.6 of Green eMotion. The results of the fundamental economic impact analysis of EV rollout will inform the gap analysis through identifying the key sources of value of flexible EV charging management that can then be contrasted to whether these can be captured using present market and regulatory arrangements. A particular challenge in this context is whether the overall optimal outcome for the system can be delivered through energy prices only. Efficient approaches to price-based control are an outstanding research question (as investigated for instance in [33] and [34]) and will therefore be addressed in Deliverables 9.6 and 9.7.

Realising the value of smart EV charging would require the incorporation of highly distributed EVs into system operation, while exposing EV owners to varying prices or external control. This represents a paradigm change compared to today's approach to electricity system management, based on asset redundancy for network assets and control of a modest number of large-scale generators in real-time operation. The gap analysis will therefore investigate which aspects of current arrangements represent the most significant barriers to an efficient widespread rollout of EVs.

4.4 Relevance for policy recommendations

Similar to informing the gap analysis, the quantitative case studies from this report will also provide insights needed for developing policy recommendations for a broad rollout of electromobility that are the key focus of Deliverable 9.7 of Green eMotion. Among other topics, this report is expected to propose solutions and mechanisms that are capable of rewarding flexibility of EVs for providing multiple services, the economic value of which has been quantified in this report.

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Appendix 1: Whole-system methodology for assessing the impact of electromobility on electricity systems

This Appendix presents a novel whole-systems approach to understanding the simultaneous impact of EVs on both system operation and necessary investment in new infrastructure capacity, including generation, transmission and distribution. This assessment is performed within a single analytical framework capable of simultaneously considering the impact of EVs on different segments of the electricity system.

The impact of a high uptake of EVs in a system is analysed within a single analytical framework, which can reveal trade-offs between objectives in various sectors pursued by controlled EV charging strategies, for different future development scenarios, both on EV and energy system side. This approach has the potential to close the gap in analysing the system impact of EVs and inform the EU policy makers, regulators and the wider industry about the appropriate commercial and regulatory arrangements to facilitate a cost-effective integration of EVs in the existing and future electricity infrastructure.

The Appendix first highlights the necessity to adopt a whole-systems approach when assessing the impact of massive rollout of EVs in future low-carbon electricity systems, and describes the Dynamic System Investment Model (DSIM), which has been specifically designed by Imperial College London to perform this type of analysis. Given that one of the key impacts of large-scale uptake of electro-mobility is expected to be reflected in increased distribution network reinforcement cost, we use our advanced approach to estimating the distribution reinforcement cost on a national scale using the concept of statistically representative networks (described in more detail in Appendix 2). The information on the necessary levels of reinforcement as a function of demand levels in a given scenario is provided as an input into the DSIM model, enabling it to make cost-optimal decisions on the deployment and utilisation of flexible technologies in order to minimise the overall system cost.

The description of our modelling approach is concluded with the description of EV demand modelling in our whole-systems analytical model, including the flexibility of EVs, while also reflecting on the impact of other flexible demand technologies. All flexible demand categories are studied in detail using dedicated bottom-up models that enable the quantification of the flexibility potentially provided by these technologies, while maintaining the level and quality of service they provide to end-consumers.

Our approach to quantifying the impact of EVs considers total system cost (including both investment and operation) for a given generation and demand scenario, and is capable of comparing the cases when the model is allowed to apply “smart” EV charging strategies and those where charging is not coordinated in any way. The value of smart charging, i.e. the reduction in total system cost as a result of deploying alternative charging strategies will provide valuable insights into the areas where EVs can provide system benefits, potentially helping to shape future commercial and regulatory arrangements so as to enable the efficient mass roll-out of electro-mobility across Europe.

Whole-systems assessment approach

When considering the system impact of large-scale penetrations of EVs it is important to consider two key aspects:

- **Different time horizons**: from long-term investment-related time horizon to real-time balancing on a second-by-second scale (Figure A1.1); this is important as various flexible balancing technologies (such as smart EV charging) can both contribute to savings in generation and network investment as well as increase the efficiency of system operation.

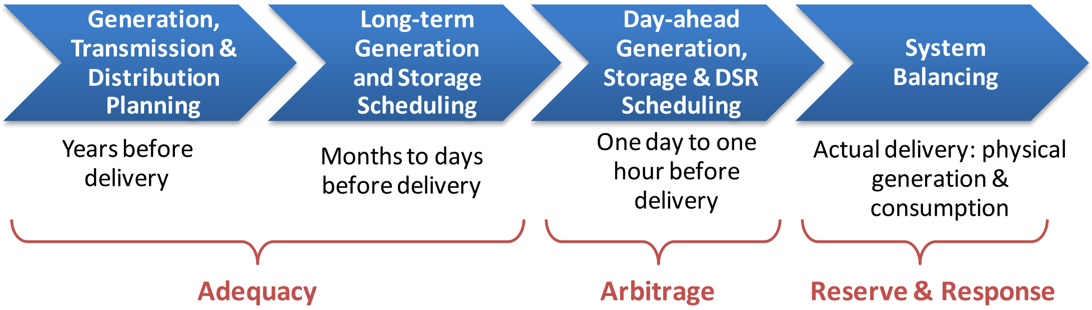


Figure A1.1 Balancing electricity supply and demand across different time horizons

- **Different assets in the electricity system**: generation assets (from large-scale to distributed small-scale), transmission network (national and interconnections), and local distribution network operating at various voltage levels (Figure A1.2). This is important as different balancing technologies may be placed at different locations in the system and at different scales. For example, bulk storage technologies such as pumped-storage hydro plants are normally connected to the national transmission network, while (flexible) EVs are connected to local low-voltage distribution networks.

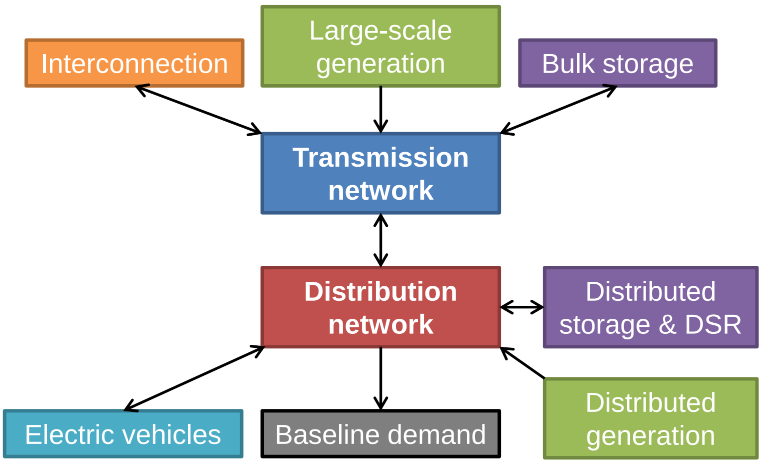


Figure A1.2 Interactions between different segments of electricity system

Time and location effects

The interactions between different time scales and across different asset types are essential for the analysis of future low-carbon electricity systems that include alternative balancing technologies such as smart EV charging, energy storage and demand-side response. Clearly, applications of those enabling technologies in the system can improve not only the economics of short-run system operation, but they can also reduce the necessary investment into generation and network capacity in the long-run.

In order to capture these effects and potential trade-offs between different flexible technologies, it is critical that they are all modelled in a single integrated modelling framework. To meet this requirement Imperial College London has developed *DSIM*, a comprehensive system analysis tool which is able to simultaneously balance long-term investment decisions against short-term operation decisions, across generation, transmission and distribution systems, in an integrated fashion.

This holistic model provides optimal decisions for investing into generation, network and/or storage capacity (both in terms of volume and location), in order to satisfy the supply-demand balance in an economically optimal way, while at the same time ensuring efficient levels of security of supply. The DSIM model has been significantly enhanced as part of the R&D work involved in producing this deliverable, enabling DSIM to estimate distribution network reinforcement cost driven by EV deployment in a number of EU countries, quantify the new demand for EV charging as well as consider different approach to smart charging control.

Capturing investment and operation decisions within a single modelling framework

A clear advantage of DSIM over most traditional models is that it is able to simultaneously consider system operation decisions and capacity additions to the system, with the ability to quantify trade-offs of using alternative mitigation measures, such as e.g. smart EV management, for real-time balancing and transmission and distribution network and/or generation reinforcement management.

Based on the input information on hourly demand profiles, generation parameters and starting network configuration, the model provides the optimal decisions for investing into generation, network and/or storage capacity (both in terms of volume and location), in order to satisfy the supply-demand balance in an economically optimal way, while also meeting the security of supply criteria.

Furthermore, this model is also capable of capturing and quantifying the necessary investments in distribution networks in order to meet demand and/or distributed generation growth (e.g. through electrification of transport sector), with the additional capability to optimise the flexible EV charging management if it is available as an option in the system. This has been made possible by coupling DSIM with a costing model for distribution network reinforcement based on calibrated representative low-voltage (LV) and high-voltage (HV) distribution networks. This approach has also been developed by Imperial College London and is presented in more detail in Appendix 2. Representative networks capture the statistical properties of typical network topologies ranging from high load density urban networks to very low load density rural networks. The key design parameters of the representative networks are comparable with those of real distribution networks of similar topologies, particularly in terms consumer and load density, ratings of feeders and transformers used, associated network lengths and costs.

Opportunities for EVs to simultaneously generate benefits in multiple segments of electricity system

The DSIM model is used to perform the analysis in this report and investigate the simultaneous impact of various EV charging approaches on the entire electricity system cost performance at the European level: generation investment, transmission investment, distribution investment, and real-time balancing of the system. Because of these features, the model can capture various trade-offs associated with EV charging control across different time horizons and asset types, such as the potential conflicts and synergies between different applications of smart EV charging, for example in supporting intermittency management at the national level on one hand, and reducing necessary reinforcements in the local distribution network on the other.

Depending on the analysed system one might expect to encounter both synergies and conflicts between pursuing different objectives in various subsectors of the electricity system. For instance, charging the batteries during night hours will help to avoid an increased peak demand at the system level, which will translate into lower generation and transmission capacity requirements and potentially also lower operating cost, but will also help reduce peak demand in local distribution networks. This is an obvious example of synergistic effects of controlled EV charging on reducing the system cost. If on the other hand EVs try to follow the fluctuating wind output at the same time, and there is a surge in wind output during system peak demand hours, some EV demand may be shifted to those hours in order to capture the abundant (and low marginal-cost) wind energy. This will, however, cause an increase in local peaks (and potentially require additional investment into network reinforcement), resulting in conflicting objectives i.e. the necessity to find a compromise strategy instead of following either of the two objectives separately. The optimal long-term trade-off in this context is found by the DSIM model through balancing the short-term operation cost against long-term investments in a range of assets.

Dynamic System Investment Model (DSIM)

The integrated optimisation of electricity system planning and operation in DSIM is formulated as a linear programming problem and implemented in the FICO Xpress environment [6]. DSIM considers two different time horizons: (i) short-term operation with a typical resolution of one hour or half an hour, which is coupled with (ii) long-term investment i.e. planning decisions with the time horizon of typically one year (the time horizons can be easily adjusted if needed). All annual investment decisions and 8,760 hourly operation decisions are determined simultaneously in order to guarantee the overall optimality of the solution. The size of a DSIM optimisation problem can therefore become very large for a complex interconnected system, involving millions of variables and constraints. An overview of the DSIM model structure is given in Figure A1.3.

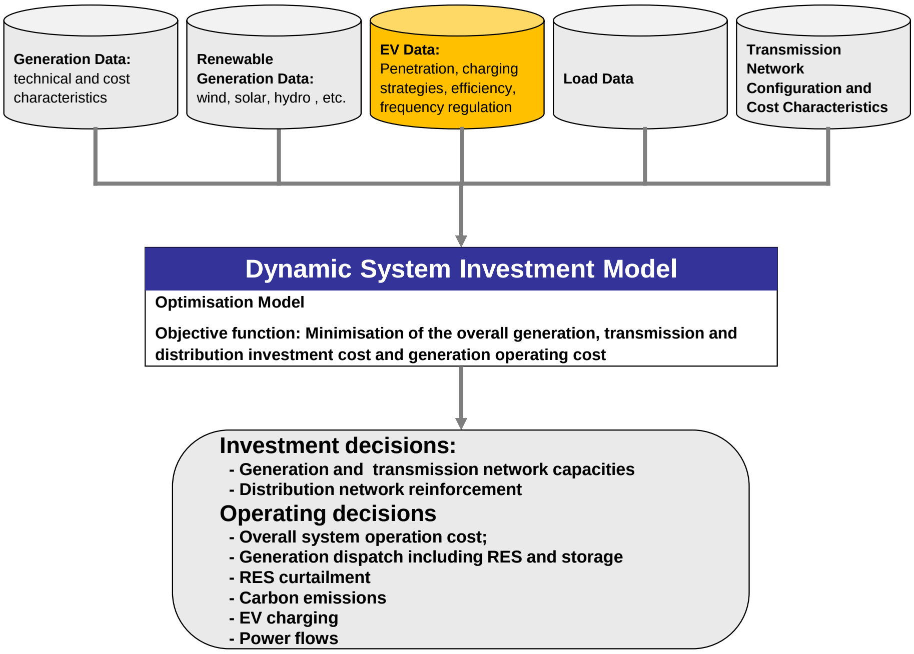


Figure A1.3 Structure of the Dynamic System Investment Model (DSIM)

Objective function

The objective function of DSIM is to minimise the overall system cost, which consists of investment and operating cost:

- **Investment cost** includes (annualised) capital cost of new generating and storage units, capital cost of new interconnection capacity, and the reinforcement cost of transmission and distribution networks. Various types of investment costs are annualised by using the appropriate Weighted-Average Cost of Capital (WACC) and the estimated economic life of the asset. Both of these parameters are provided as inputs to the model, and their values can vary significantly between different technologies.

- **System operating cost** consists of the annual generation operating cost and the cost of energy not served (load-shedding). Generation operating cost consists of: (i) variable cost which is a function of electricity output, (ii) no-load cost which is a function of a number of synchronised units, and (iii) start-up cost. Generation operating cost is determined by two input parameters: fuel prices and carbon prices (for technologies which are carbon emitters).

Constraints

There are a number of equality and inequality constraints that are considered in the model while minimising the overall cost.

<u>System-level constraints</u>

- *Power balance constraints*: ensure that supply and demand are balanced at any time.
- *Operating reserve constraints*: include various forms of fast and slow reserve constraints. The amount of operating reserve requirement is calculated as a function of uncertainty in generation and demand across various time horizons. The model

distinguishes between two basic reserve types: (i) fast reserve or frequency response, which is delivered in the timeframe of a few seconds to 30 minutes; and (ii) slow reserve, typically split between spinning and standing reserve, with delivery occurring within the timeframe of half an hour to several hours after the request. In this study, we use three standard deviations of wind variability for 4-hour variability to calculate the additional slow reserve requirements due to wind uncertainty, and 15 minutes variation to calculate the additional fast reserve (response) requirement. Calculation of reserve and response requirements for a given level of intermittent renewable generation is carried out exogenously and provided as input into the model. DSIM then schedules the optimal provision of reserve and response services, taking into account the capabilities and costs of potential providers of these services (response slopes, efficiency losses of part loaded plant etc.) and finding the optimal trade-off between the cost of generating electricity to supply a given demand profile, and the cost of procuring sufficient levels of reserve and response (this also includes alternative balancing technologies such as storage and DSR as appropriate).

In DSIM, frequency response can potentially be provided by:

- Synchronised part-loaded generating units
- Interruptible charging of electric vehicles. We assume a percentage of EV charging can be used as frequency response.
- A proportion of wind power being curtailed
- A proportion of electricity storage when charging (similar to EV)
- Smart refrigeration

While reserve services can be provided by:

- Synchronised generators
- Wind power or solar power being curtailed
- Stand-by fast generating units (OCGT)
- Electricity storage
- A proportion of interruptible heat storage when charging

The amount of spinning and standing reserve and response is optimized ex-ante to minimise the expected cost of providing these services, and we use additional advanced stochastic generation scheduling models developed at Imperial College London ([7], [8]) to calibrate the amount of reserve and response scheduled in DSIM. These stochastic models find the cost-optimal levels of reserve and response by performing a probabilistic simulation of the actual utilisation of these services.

- *Emission constraints*: limit the amount of carbon emissions within one year. Depending on the severity of these constraints, they will have an effect of reducing the electricity production of plants with high emission factors such as oil or coal-fired power plants. Emission constraints may also result in additional investment into low-carbon technologies such as nuclear or CCS in order to meet the constraints.
- *Security constraints*: ensure that there is sufficient generating capacity in the system to supply the demand with a given level of security. Using these constraints, the model measures the generation capacity margin and estimates the Loss of Load

Probability (LOLP) index. The maximum annual Loss of Load Expectation (LOLE)[21] is constrained not to exceed a pre-defined value provided as an input (in most studies we use 4 hours as maximum LOLE). If there is storage in the system, DSIM uses its capacity for security purposes if it can contribute to reducing peak demand.

An interesting feature of the security constraints in DSIM is that they allow the capacity from other regions to contribute to security i.e. to increase the domestic generating capacity margin. However, this contribution is limited by the capacity of interconnection between the regions. Furthermore, by providing security to other regions, the contributing regions suffer reductions in their own capacity margins, and this will in effect limit the amount of capacity that can be shared with other regions. This feature allows for the security-related benefits of interconnection to be adequately quantified [9]. Conversely, it is possible to specify in DSIM that no contribution to security is allowed from other regions, which will clearly increase the system cost, but will also provide an estimate of the value of allowing the interconnection to be used for providing system security.

Generator-level constraints

- *Generator operating constraints*: (i) Minimum Stable Generation (MSG) and maximum output constraints; (ii) ramp-up and ramp-down constraints; (ii) minimum up and down time constraints; and (iv) available frequency response and reserve constraints. In order to keep the size of the problem manageable, we group generators according to technologies, and assume a generic size of a thermal unit of 500 MW (the model can however commit response services to deal with larger losses, e.g. 1,800 MW as used in the model). The model captures the fact that the provision of frequency response is more demanding than providing operating reserve. Only a fraction of the headroom created by part-loaded operation can therefore be used for frequency regulation, as indicated in Figure A1.4. Given that the functional relationship between the available response and the reduced generation output has a slope with an absolute value considerably lower than 1, the maximum amount of frequency regulation that a generator can provide (R_{max}) is generally lower than the headroom created from part-loaded operation (P_{max} – MSG).

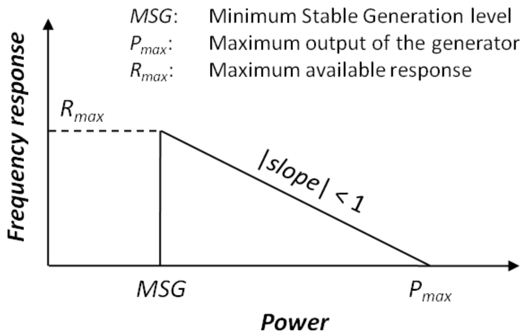


Figure A1.4 Provision of frequency regulation from conventional generation

Hence, one of important DSIM capabilities is to quantify the cost of generation operating constraints, which can be quantified by comparing the generation operating cost with and without the constraint in question being considered by the model. For

[21] LOLE is the expected number of hours when electricity demand exceeds available electricity supply capacity.

example, it is possible to use DSIM to quantify the benefits of flexible generators that can increase or decrease power more rapidly and can provide higher amount of frequency response at lower cost. Another example is to use DSIM to quantify the benefits of wind power generation providing frequency response services.

- *Generation capacity*: DSIM optimises the investment in new generation capacity while considering the generators' operation costs and CO_2 emission constraints, and maintaining the required levels of security of supply. DSIM optimises both the quantity and the location of new generation capacity as a part of the overall cost minimisation. If required, the model can limit the investment in particular generation technologies at given locations.
- *Annual load factor constraints*: can be used to limit the utilisation level of thermal generating units, e.g. to account for the effect of planned annual maintenance on plant utilisation.
- For *wind, solar, marine, and hydro run-of-river* generators (with no reservoirs), the maximum electricity production is limited by the available energy profile, which is specified as part of the input data. The model will maximise the utilisation of these units (given zero or low marginal cost). In certain conditions when there is oversupply of electricity in the system or reserve/response requirements limit the amount of renewable generation that can be accommodated, it might become necessary to curtail their electricity output in order to balance the system, and the model accurately accounts for this.
- For *hydro generators with reservoirs and pumped-storage units*, the electricity production is limited not only by their maximum power output, but also by the energy available in the reservoir at a particular time (while optimising the operation of storage). The amount of energy in the reservoir at any given time is limited by the size of the reservoir. It is also possible to apply minimum energy constraints in DSIM to ensure that a minimum amount of energy is maintained in the reservoir, for example to ensure the stability of the plant. For pumped storage, DSIM also takes into account the efficiency losses during charging and discharging, which results in less energy being discharged from the storage than what has been charged into the storage.

Demand-level constraints

- *Demand-side response constraints* include constraints for various specific types of loads. DSIM broadly distinguishes between the following electricity demand categories: (i) weather-independent demand, such as e.g. lighting, industrial demand etc., (ii) heat-driven electricity demand, (iii) demand for EV charging, and (iv) smart appliances' demand. Different demand categories are associated with different levels of flexibility. The constraints ensure that the amount of daily energy consumption of flexible demand after the optimisation is at least equal to the energy defined by the non-modified consumption profile specified in the input data. Losses due to temporal shifting of demand are modelled if required. Other constraints ensure that the maximum amount of energy that can be shifted within a day and at any time interval is limited by the flexibility parameters provided as input data. These flexibility parameters are obtained using detailed bottom-up modelling of different types of flexible demand, as described in more detail in Section "Other demand-side response technologies" on page 88.

<u>Network-level constraints</u>

- *Power flow constraints* limit the energy flowing through the lines between the areas in the system, using the installed capacity of lines as the upper bound (DSIM can handle power flow constraints in each flow direction). If instructed to do so, the model can choose to enlarge line capacities if this is cost-efficient. Expanding transmission and interconnection capacity is generally found to be vital for facilitating an efficient integration of large intermittent renewable resources. Interconnectors provide access to renewable energy and improve the diversity of demand and renewable output on both side of the interconnector, thus reducing the short-term reserve requirement. Interconnection also allows for sharing of reserves, which reduces the long-term capacity requirements.
- *Distribution network peak load constraints* are devised to determine the level of distribution network reinforcement cost, as informed by detailed modelling of representative networks for the analysed system (see Appendix 2). DSIM can model different types of distribution networks, e.g. urban, rural, etc. with their respective reinforcement cost.

User-defined policy aspects

There are further specific constraints that can be activated in DSIM for the purpose of studying the impact of various strategic policy-related objectives:

- *Self-sufficiency* in terms of capacity, i.e. there is no contribution from one region to the capacity margin in other regions and vice versa. This can be used to reflect different levels of integration of reserve capacity market in Europe i.e. whether reserve can be shared across interconnection if economically efficient, simultaneously to energy exchanges.

- *Energy neutrality*. This means that the net annual energy import into a given region is zero. It allows the region to import power from and export to other regions as long as the annual net balance is zero. It can be used to reflect the energy policy of a given country or region that does not allow reliance on (net) energy imports.

System topology and geographical scope

The interconnected European electricity system that is used for studying the impact of EVs is illustrated in Figure A1.5. It is based on a high-level representation of European national systems, with typically several nodes used to represent larger countries, and one node for smaller countries.

This representation will allow drawing conclusions on the impact of EV charging on a pan-European level, such as the level of optimal generation and transmission capacity additions to accommodate demand growth resulting from various EV charging strategies.

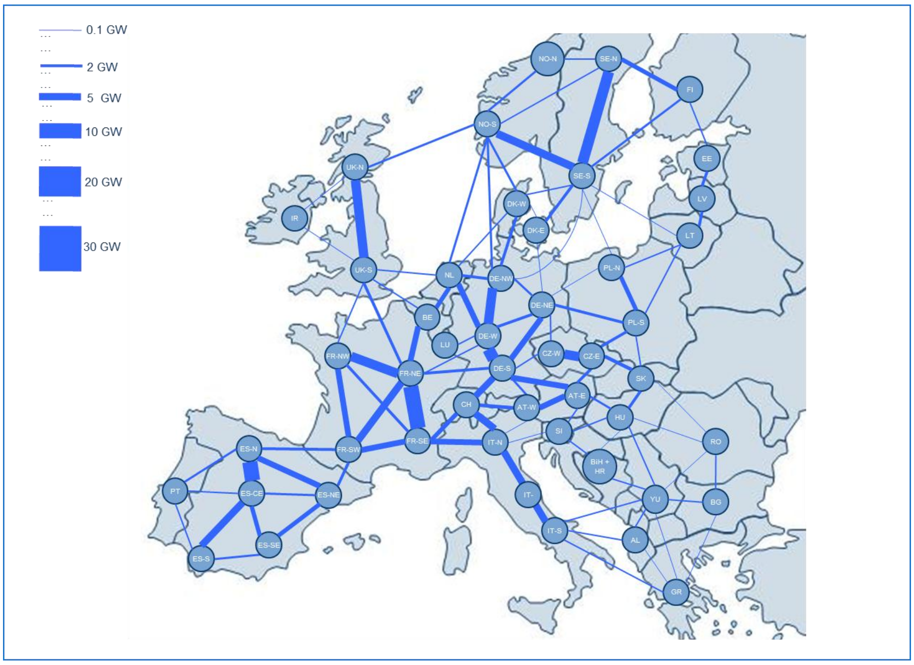


Figure A1.5 System topology for studying the impact of EVs in Europe

Distribution network investment modelling

Including a detailed representation of distribution networks in various European countries into the European level assessment would result in a prohibitively complex model with potentially millions of nodes. Therefore, the approach to evaluating the distribution network reinforcement cost adopted in this study is based on the *statistically representative networks* approach, where networks are represented on a country or regional level according to the key statistical properties of different network types. Generating these representative networks is based on actual detailed statistical data from EU countries on population densities and land areas across a large number of smaller administrative units (municipalities, districts etc.).

The reinforcement cost of each representative network in a given scenario is estimated as the function of peak demand, and this information is provided as input into DSIM to perform an overall system cost assessment. The resulting total reinforcement cost represents a very good estimate of the total reinforcement cost of actual distribution networks, as elaborated in the Appendix.

Based on the information on the statistical analysis of population density, we have generated a set of typical networks using Imperial's fractal tool that can be expected to be representative of the real situation in each country. These representative networks then provide the basis for the detailed distribution analysis and the evaluation of network reinforcement costs.

Examples of different consumer patterns / layouts that can be created by specifying the desired layout parameters are shown in Figure A1.6 for urban, sub-urban and rural layouts. In this procedure the parameters of representative networks are chosen to calibrate them against the actual distribution networks of the analysed system.

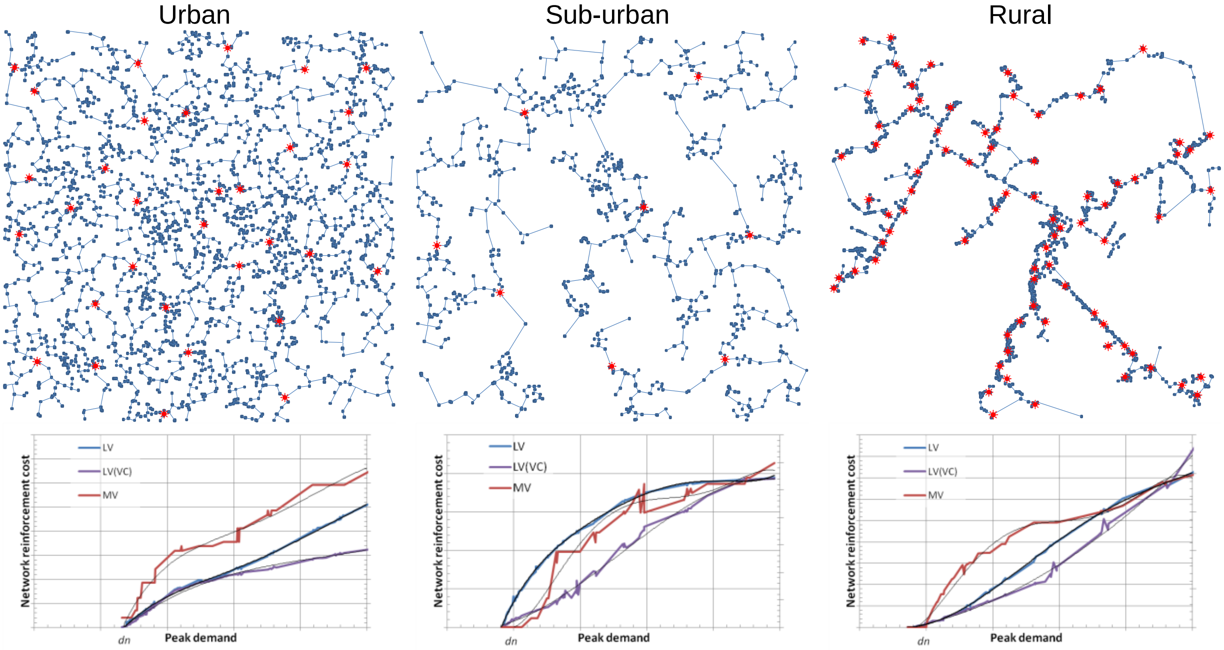


Figure A1.6 Examples of generated network layouts and corresponding reinforcement cost functions

For each network layout a reinforcement cost curve can be quantified that links the necessary investment with the level of peak demand observed in the system. Given that peak demand in distribution networks can be significantly affected by different EV charging strategies, the impact of widespread EV deployment, and in particular of different charging control strategies, can be quantified with a considerable level of accuracy using this approach. The network reinforcement cost curve is included in DSIM alongside other operation and investment cost categories, which allows for finding optimal trade-offs between EV charging aimed at mitigating distribution network reinforcement versus charging to improve the efficiency of other segments of the electricity system.

Parameterisation of statistically representative distribution networks was based on a comprehensive data set for close to 100,000 administrative units in the EU-27, for which population densities and areas were available. The administrative areas in a given country were grouped into different density classes, which were associated with different portfolios of distribution networks. Using different network classes and calibrating their number and assumptions on their typical design (such as network length, number of connections or installed transformation capacity per km^2), we were able to derive an estimate of the overall distribution infrastructure in a given country. This information was then compared against available evidence from each country to maximise the accuracy of representative network approximation. More details on the modelling of distribution networks in this analysis are provided in Appendix 2.

Quantifying EV demand

EV loads are particularly well placed to support system operation, given the relatively modest amount of energy needed daily, generally short driving times, and relatively high power ratings expected for EV batteries [3]. Our models have the capability to quantify how much of EV charging demand can be shifted to times that are more efficient from the system perspective, ensuring at the same time that passengers are still able to complete all of their intended daily journeys.

Vehicle driving patterns

Modelling of EVs is based on the statistics of national driving patterns. In order to quantify the impact of EV charging on the future electricity system, it is essential to understand the typical behaviour of vehicle users, in particular the driving patterns and on-road times for the light vehicle fleet. This behaviour will obviously be influenced by mobility requirements of vehicle users, such as commuting to work and back, going for shopping, leisure activities etc.

A typical input into the modelling of EVs is the National Transport Survey (NTS) data, containing information on all journeys conducted by a sample of light vehicles representing the national vehicle fleet, including starting and ending times of individual journeys grouped according to the distances travelled. As illustrated in Table A1.1 on a sample collected in the UK, journey data can be classified into distance bands, e.g. less than 1 mile, 1 to 2 miles, 2 to 3 miles etc.

Table A1.1 Sample of driving parameters for the passenger vehicle fleet

Start time	End time	Distance band	No. of journeys (daily)
00:00 – 00:59	00:00 – 00:59	Under 1 mile	6,922
00:00 – 00:59	00:00 – 00:59	1 to under 2 miles	15,987
00:00 – 00:59	00:00 – 00:59	2 to under 3 miles	14,848
…	…	…	…
00:00 – 00:59	01:00 – 01:59	2 to under 3 miles	1,277
00:00 – 00:59	01:00 – 01:59	3 to under 5 miles	4,938
00:00 – 00:59	01:00 – 01:59	5 to under 10 miles	3,209
…	…	…	…
00:00 – 00:59	02:00 – 02:59	50 to under 100 miles	474
00:00 – 00:59	03:00 – 03:59	100 to under 200 miles	492
00:00 – 00:59	04:00 – 04:59	200 miles and over	388
…	…	…	…
23:00 – 2359	23:00 – 23:59	25 to under 35 miles	7,750
23:00 – 2359	23:00 – 23:59	35 to under 50 miles	1,458
23:00 – 2359	23:00 – 23:59	50 to under 100 miles	923

Source: UK Department for Transport, National Travel Survey Database 2008

The number of possible combinations of journey categories (characterised by start and end times and the mileage involved) that a vehicle could carry out during a day is potentially very large, requiring extensive computational time to analyse the system. The driving data are therefore processed and aggregated in order to obtain the representation of driving behaviour which is still detailed and realistic, but is also manageable from the computational point of view.

In order to reduce the number of journey categories, the distance bands are grouped into three clusters: Short, Medium and Long. The concept of "equivalent distance" is further introduced, serving as the representative distance driven within a particular type of journey. For instance, all journeys classified as Short (between 0 and 24 km) are represented by an equivalent distance of 14 km each. Similarly, the values of 32 and 160 km are representative for Medium and Long journeys, respectively. These values have been calibrated to ensure that the total distance driven remains the same as the one in the starting journey database.

One of the findings emerging from the journey database is that each vehicle makes on average two journeys a day. This seems in accordance with the intuitive perception of using vehicles for commuting, i.e. making journeys from home to workplace and back every day. In order to facilitate the introduction of EV energy requirements in the power system modelling framework, it is assumed that each vehicle in the fleet completes exactly two journeys. The journey data is therefore processed so that for each pair of journey categories, the following specific information is identified that will be used as input for the optimisation procedure:

- Start and end times of journeys, defining when the vehicle is on the road i.e. when it is stationary and thus potentially available for charging management.
- The number of vehicles involved and the corresponding energy requirements for each journey combination, determining the power and energy constraints for the vehicles during their stationary period.

The first step in pre-processing the journey data is to determine which journey combinations are allowed with respect to their start/end times: since two journeys are physically taken by a single car, they cannot overlap. Allocating vehicles across all eligible journey combinations is carried out by proportionately distributing vehicles completing a given first journey across all eligible second journeys in proportion to the number of vehicles contained in those eligible (non-overlapping) second journeys. Formal description of the algorithm used to quantify the number of vehicles following each eligible journey pattern can be found in [10]. An illustrative sample from this dataset is presented in Table A1.2. The energy requirements for the two journeys in each category are easily evaluated by multiplying the number of vehicles involved with the length of the equivalent journey for a given journey type and the specific EV consumption.

Table A1.2 Sample of processed journey data

Journey1	Journey2	Start1	End1	Start2	End2	No. of EVs
…	…	…	…	…	…	…
Short	Short	8	9	17	18	84,634
Short	Short	8	9	17	19	34,858
Short	Short	8	9	17	20	215
Short	Short	8	9	18	19	93,793
Short	Short	8	9	18	20	32,743
Short	Short	8	9	18	21	209
Short	Short	8	9	19	20	66,669
Short	Short	8	9	19	21	21,123
Short	Short	8	9	19	22	148
Short	Short	8	9	19	23	13
Short	Medium	8	9	17	18	11,792
Short	Medium	8	9	17	19	28,923
Short	Medium	8	9	17	20	2,112
Short	Medium	8	9	17	21	97
Short	Medium	8	9	17	22	39
Short	Medium	8	9	17	23	39
Short	Medium	8	9	18	19	15,444
Short	Medium	8	9	18	20	29,183
Short	Medium	8	9	18	21	1,888
Short	Medium	8	9	18	22	75
Short	Medium	8	9	18	23	41
Short	Medium	8	9	19	20	10,821
Short	Medium	8	9	19	21	14,268
Short	Medium	8	9	19	22	662
…	…	…	…	…	…	…

The dataset in Table A1.2 fully describes the daily behaviour of the entire national fleet of vehicles (assuming 100% penetration of EVs), enabling the identification of both stationary and on-road times for any group of vehicles following a certain journey combination. In order to simulate EV penetrations lower than 100%, the last column (and the corresponding energy requirements) in Table A1.2 is reduced when running case studies using a factor representing the actual EV penetration.

The above journey dataset describes the average daily behaviour based on annual data. In reality, journey patterns will tend to exhibit variations both across seasons and within a week. For instance, driving patterns during workdays are more likely to be dominated by commuting cycles, i.e. travelling to work and back, with the most intensive driving activities occurring around morning and afternoon rush hours. During the weekends on the other hand, the driving patterns are more likely to be dictated by leisure activities rather than commuting requirements. The difference between typical driving patterns for workdays and weekends is illustrated in Figure A1.7, which also suggests that fewer journeys are undertaken during weekends than on workdays.

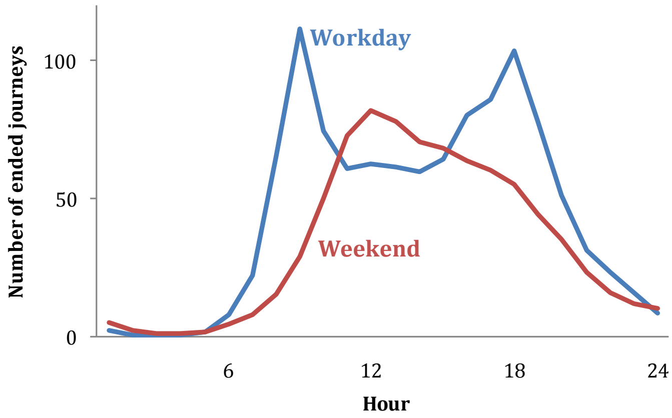


Figure A1.7 Example of weekly variations in driving patterns

The input data on EV demand have also been verified against the data collected in GeM Demo Regions to ensure they are generally coherent. Nevertheless, given that only about 10% of vehicles in those regions can be associated with private users (the remainder are captive fleets, business fleets and rental vehicles), this data was not used as the only source of information given that the focus of this analysis is on a mass rollout of EVs with particular emphasis on household users.

Energy requirements for battery charging

In order to assess the electricity requirements for a fleet of EVs, it is necessary to establish a link between the mileage driven by an electric vehicle and the amount of electricity needed to travel the required distance. Reference [4] uses a specific energy consumption of 0.16 kWh/km, although the value of 0.11 kWh/km is also reported; while [11] uses 0.20 kWh/km. Reference [12] differentiates the consumption between various types of EV: 0.13-0.25 kWh/km for a smaller EV, 0.12-0.16 kWh/km for a larger EV, and 0.15-0.25 kWh/km for a Plug-in Hybrid EV (PHEV). In this report we assume the consumption of 0.15 kWh/km (which does not include any losses in EV charging equipment or other on-board consumption such as heating or air conditioning etc.). For the example of a vehicle making on average 30 km per day, this translates into the average daily energy requirement of 4.5 kWh. In order to focus on the high-level impact of EVs on the electricity system, only one generic type of EVs is considered in this paper.

Average annual distance driven per EV was assumed at 12,300 km. This value lies broadly between the values reported e.g. for the UK (12,600 km) in [13] and Germany (11,800 km) in [14].

We typically envisage two approaches to charging EVs: uncontrolled and optimised in real-time. The first approach is where EV charging is done on demand. Such a policy may increase peak demand significantly, although the extra energy needed is relatively small. The second approach is to optimise EV charging in real-time by making charging part of a communication and control infrastructure and utilising the inherent flexibility of EV demand to be shifted in time. Coordinated EV charging has the potential to reduce a range of system cost categories, ranging from reduced operating cost to lower CAPEX expenditure to ensure a secure operation of the system ([15], [16], [17]).

In the uncontrolled approach to EV charging, the timing of charging is not chosen to support system operation, but is rather a consequence of daily vehicle usage patterns, i.e. driven by users' convenience. Under this charging scheme all users are allowed to charge their vehicles as and when they wish, with no control being exercised on the charging process by the system operator or any other third party.

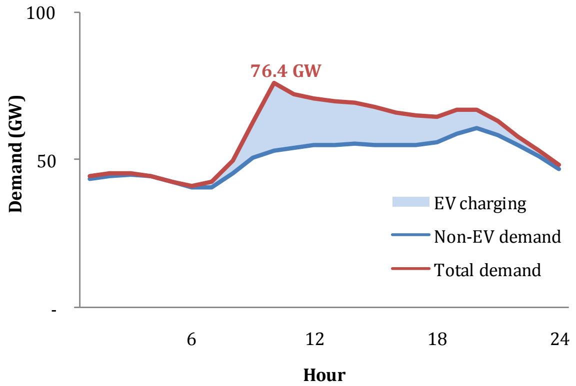
Following the assumption that each vehicle completes two journeys per day, it is possible to formulate the following heuristic charging strategies in order to assess the aggregate EV consumption:

- **After 1st**: all vehicles charge their batteries after completing their first journey in the day, storing the energy required to complete both daily journeys.

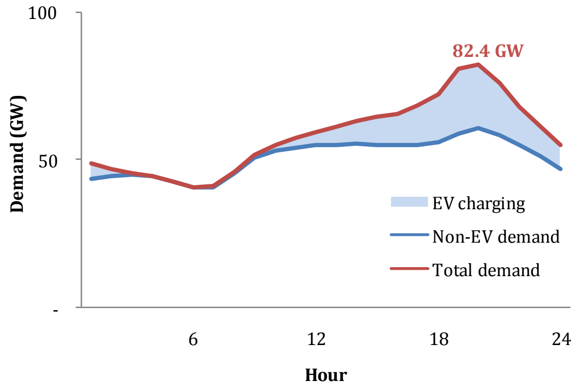
- **After 2nd**: all vehicles charge their batteries after completing their second journey in the day, storing the energy required to complete both daily journeys.

- **After 1st and 2nd**: all vehicles charge their batteries twice per day; the first charging takes place after completing the first journey, and the energy involved is equal to the one consumed in that first journey. Similarly, the second charging takes place after the second journey, with the stored energy being equal to the consumption of the second journey.

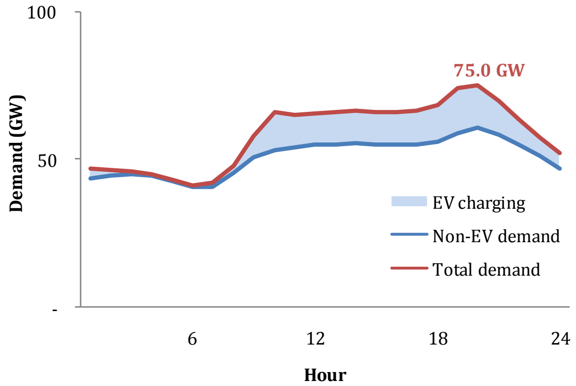
The impact of the three non-optimal EV charging strategies is illustrated in an example in Figure A1.8, where the additional EV load is plotted on top of the existing GB system load diagram for a typical winter peak day (assuming 100% EV penetration to make the impact clearly visible). Similar effect could be quantified for other European electricity systems.



(a) After 1st



(b) After 2nd



(c) After 1st and 2nd

Figure A1.8 Examples of non-optimal EV charging strategies

Although the energy required to charge EV batteries within one day is the same for all three heuristic strategies, the impact on total system peak demand is the highest in the case of the "After 2nd" strategy, where a significant portion of EV load is concentrated around the time of system peak (7pm). On the other hand, the "After 1st and 2nd" strategy produces the lowest increase in system peak, as the result of EV charging load being spread more evenly within the day. For all three strategies the consumption during night hours is very small due to a low number of journeys taken in that period.

In a realistic environment with a predominantly uncontrolled charging regime, one might expect to encounter various combinations of these heuristic strategies, especially since the future EV fleet is likely to be represented by a mix of residential and commercial users. For that reason the "After 1st and 2nd" strategy will be used in this report as the default non-optimal charging strategy in order to represent the EV demand. This approach is also supported by the charging data collected in GeM Demo Regions.

Given that no control is exercised over EV charging if the non-optimal paradigm is followed, the incorporation of electrified transport load into the DSIM model is carried out in a rather straightforward manner, by adding the aggregate EV demand for a given penetration to hourly demand profiles for the original system. This results in a new total system demand that needs to be supplied by the generation resources in the system, and will incur additional cost to design and operate the system to supply the added EV demand.

Seasonal variations in driving distances appear to be of a relatively small magnitude according to the relevant transport statistics. Nevertheless, a parameter which is likely to change across seasons is the consumption per kilometre driven. This is expected to occur as a consequence of additional energy consumption for heating the vehicle in winter, and for air conditioning in summer. In this regard, a simplified assumption is made in this analysis where the baseline consumption occurring during spring and autumn months is increased by 33% to account for higher consumption during winter, and by 11% to capture the impact of air conditioning during summer. Variations in energy required between different seasons and days of week are illustrated in Figure A1.9 for the non-smart charging case. Our modelling also includes efficiency losses during battery charging.

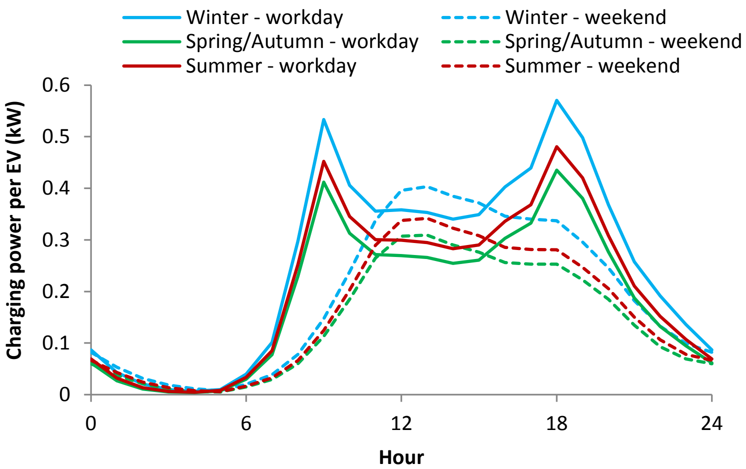


Figure A1.9 Variations in non-smart charging profiles per EV within a week and across seasons

Characterising the flexibility of EV demand

As part of the smart charging paradigm the EV charging could be managed by the system operator or by a third party (aggregator) to make the charging process economically efficient and support the operation of and investment into the system. This can be achieved in practice by e.g. exploiting the electricity price variation during peak and off-peak demand periods, as well as through provision of ancillary services by EVs when these are stationary and connected to the grid.

Figure A1.10 illustrates the possible shifting of charging demand for a single vehicle that is on the road between 7-9am and 4-8pm. These time periods are obviously not available for charging. Under an uncontrolled paradigm the EV user would plug the vehicle to be charged immediately upon completing his second journey, i.e. after returning home at 8pm. On the other hand, it may be beneficial for the system to postpone this charging until the night hours, e.g. 2-3am, which would still be more than sufficient to ensure that the user is able to make his journeys on the following day.

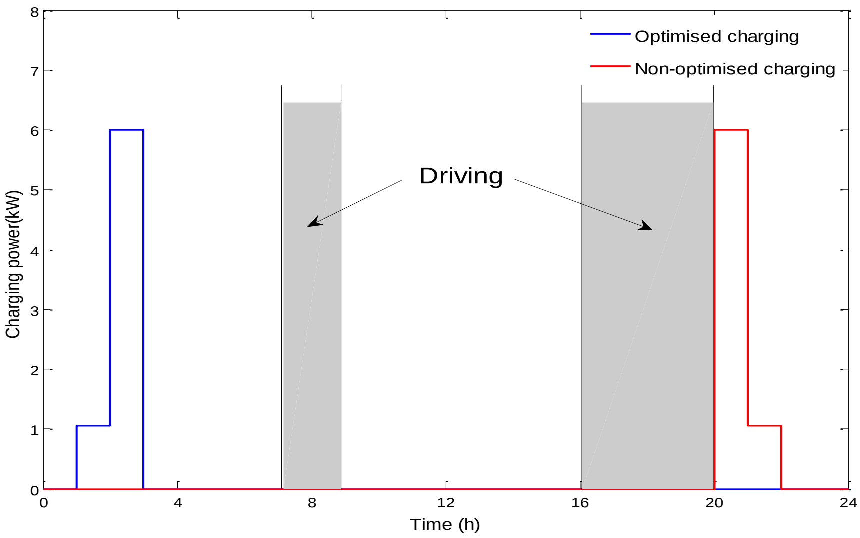


Figure A1.10 Examples of shifted charging demand for a single EV

Based on the journey data processed as described in Section "Vehicle driving patterns" (page 81), we have performed a separate analysis to establish the volume of uncontrolled EV demand (depicted in Figure A1.8) that can be shifted in time in order to enhance system operation and design. Our finding was that a very high percentage of EV demand can be shifted to night time without any impact on the users' mobility requirements i.e. with users till being able to make their usual journeys. This proportion was found to vary between 92% during winter to over 99% during spring and autumn months. These percentages represent the flexibility parameters that serve as an input to the part of the DSIM model which determines the actions of demand-side response (see page 73).

Other demand-side response technologies

It is expected that in addition to electromobility, other new demand categories such as electrified heating or smart domestic appliances will play an increasingly important role in decarbonising the electricity sector. Understanding the characteristics of flexible demand and quantifying the flexibility they can potentially offer to the system is vital for establishing its economic value [18]. For there to be regular flexible demand, controlled devices (or appliances) must have access to some form of storage when rescheduling their operation (e.g. thermal, chemical or mechanical energy, or storage of intermediate products). Load reduction periods are followed or preceded by load recovery, which is a function of the type of interrupted process and the type of storage. Achieving flexible demand means carefully managing this process of load reduction and load recovery. This requires bottom-up modelling of each individual appliance or device and understanding how it performs its actual function, while exploiting any flexibility that may exist without compromising the service that it delivers.

In our analysis we consider the following types of flexible demand in addition to smart EVs:

- *Smart wet appliances.* The aim of smart operation of wet appliances is to adapt, i.e. shift in time the appliance usage in response to electricity system conditions, thus providing a range of services, such as generation/demand balancing, peak reduction, and network congestion management. In this analysis we focus on three types of wet appliances: washing machines (WM), dishwashers (DW), and tumble dryers (TD). The data relevant for the use of appliances is sourced from the Smart-A project[22], and includes information such as diversified appliance demand profiles, which are important to determine when controllable demand is available, or the allowed shifting times according to consumer preferences resulting from the relevant surveys [20]. According to this input database, between 1 and 3 hours shifting is allowed for washing machines, and 1 to 6 hours for dishwashers. Figure A1.11 provides an illustration of typical diversified appliance consumption profiles for the western European countries (expressed per appliance).

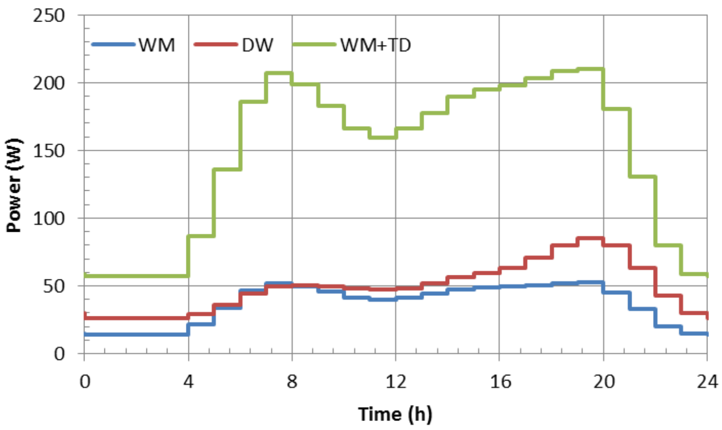


Figure A1.11 Diversified demand profiles for WM, DW and WM+TD

- *Smart refrigeration.* Refrigeration appliances can potentially contribute to providing frequency regulation services to the system, which are currently predominantly sourced from part-loaded synchronised generation [21]. If equipped with an adequate control mechanism, the appliances would be able to quickly respond to fluctuations in system frequency, such as e.g. following a loss of a major generator, by adjusting their duty cycles in such a way that their aggregate consumption helps the system to restore frequency in a way similar to large-scale generators. The difference between the behaviour of appliances and generator-based frequency regulation is that while providing the service, refrigerators deliver some of their stored energy to support the system, causing their average internal temperature to increase slightly. After some time, the temperature increase will cause the disconnected refrigerators to progressively reconnect to keep the temperature within prescribed limits. They will need energy to gradually restore their duty cycle length to the original pre-disturbance level, leading to the effect referred to as *energy payback*. Understanding the interdependency between the level and duration of service provided and energy paid back to appliances is the key to understanding their potential to support system management.

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[22] Smart-A project was an Intelligent Energy Europe project whose objective was to identify and evaluate the potential synergies that arise from coordinating energy demand of domestic appliances with local sustainable energy generation but also with the requirements of regional load management in electricity networks. More information is available on http://www.smart-a.org/.

Figure A1.12 shows how the process of load reduction and load recovery can be optimised to match the specific characteristics of the generation system.

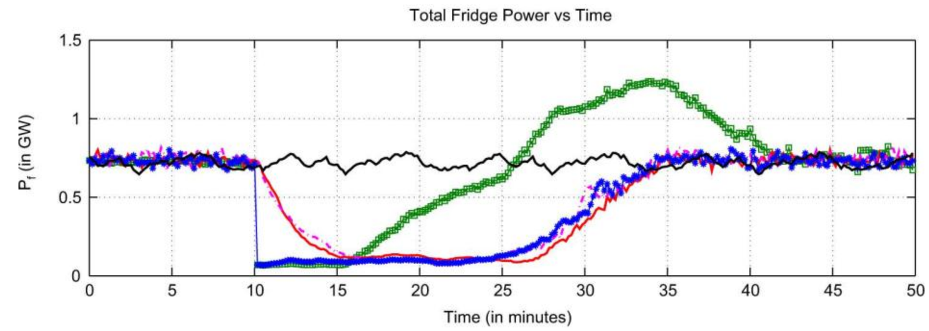


Figure A1.12 Frequency regulation using smart refrigeration [22]

By modelling the above categories of demand-side response and including them in our assessment framework, it will be possible to evaluate the performance of smart EV charging in scenarios where it has to compete with other flexible demand-side technologies in delivering system services.

Appendix 2: Quantifying distribution network investment driven by EV deployment

The purpose of distribution network modelling approach adopted in this report is to understand and quantify the impact of EV deployment on necessary network reinforcements, but also to assess the benefits of smart EV charging in avoiding or postponing network investments and compare them to potential savings generated in other segments of the electricity system. The incorporation of distribution network cost consideration into the whole-system assessment framework is discussed in the previous chapter.

This chapter explains in more detail the approach to distribution network modelling, which is based on analysing statistically representative networks rather than actual networks. This method allows us to formulate computationally feasible analytical models with only a minor sacrifice in terms of the accuracy of estimating reinforcement cost. The primary objective of the distribution analysis is therefore to estimate the need for and the cost of distribution infrastructure expansion in different scenarios and different countries as a consequence of EV rollout.

As elaborated later in this chapter, the use of statistically representative networks is motivated by the fact that the reinforcement cost in distribution networks tends to be driven by the network length, which is a function of consumer density. Using a limited number of these statistically representative network types, although not representing any particular physical networks, results in very accurate estimates of reinforcement costs in larger areas such as countries or regions.

The key steps of our overall approach to distribution network modelling can be summarised as follows:

- In the first step, we collect and process statistical information on population density (serving as proxy for load density) for a large number of smaller administrative units in each country as well as data on distribution network lengths in each country (see the section on network mapping for further details);

- This information is then used to create a set of typical networks that are representative of actual networks with respect to estimating the reinforcement cost for different European countries; and

- These representative networks then provide the basis for the detailed distribution analysis and the quantification of network reinforcement costs as a function of EV charging strategies under different scenarios.

Statistically representative networks

Our distribution investment model tests whether thermal or voltage constraints are violated and proposes appropriate upgrades of assets based on a defined reinforcement strategy. The associated upgrade cost for a given EV penetration and charging strategy (resulting in a given level of peak demand) is used to build reinforcement cost characteristics that are combined with other cost categories in DSIM, as explained in Section “Distribution network investment modelling” (page 79). The model can also include alternative network reinforcement and design strategies, quantifying the potential benefits of alternative mitigation measures such as demand response and other active network management techniques.

The developed modelling approach includes three distribution network models:

- Low Voltage (LV) network model;
- Medium Voltage (MV); and
- High Voltage (HV) networks.

The LV network model is based on representative fractal networks with the parameters that represent the key characteristics of typical LV networks supplied from individual distribution transformers. The MV network model contains feeders with a voltage of approximately 6-20 kV starting from secondary busbars in the HV/MV substations and finishing with distribution substations. The HV network finally contains assets from the Grid Supply Point, i.e. the connection to transmission (220-400 kV) or sub-transmission grids (72-132 kV) down to HV/MV transformers in primary substations.

Fractal network models

The key element of the distribution network analysis is the Fractal Distribution Networks Model (Fractal Model). The Fractal Model can create representative LV, MV and HV distribution networks that capture statistical properties of typical network topologies that range from high-load density city/town networks to low-density rural networks. The design parameters of the representative networks represent those of real distribution networks of similar topologies, for instance with regards to the number and type of consumers and load density, ratings of feeders and transformers used, associated network lengths and costs, etc.

Due to the lack of detailed information and the large degree of diversity in distribution network planning and design, it is not feasible to perform a detailed assessment of the existing distribution networks in different European countries within this project. Nevertheless, experience has shown that it is possible to represent real networks through a limited number of typical networks with statistically similar network configurations. This approach allows for a number of design policies to be tested on a network with the same statistical properties as the network of interest, with only a minor sacrifice in terms of accuracy of reinforcement cost estimates. Moreover, any conclusions reached are applicable to other areas with similar characteristics.

For this purpose, we rely on a limited number of typical representative LV networks, such as those typical for urban, semi-urban, semi-rural, or rural areas. Our fractal LV network models have the capability to characterise statistically representative networks, i.e. to generate many statistically similar networks (in terms of key network parameters) that resemble different area types, thus allowing statistically significant conclusions to be drawn. These models can reproduce realistic network topologies and particularly network lengths, which represent one of the main drivers for the cost of network reinforcement.

The procedure of generating representative networks consists of the following steps: (i) creation of consumer layouts, (ii) generation of supply networks, and (iii) supply network design [23]. Examples of the different consumer patterns / layouts that can be created by specifying desired capacity dimension of a fractal (i.e. Fractal Dimension or FD) are shown in Figure A2.1 for different (typical) urban, rural and intermediate layouts. These consumer patterns are characterised by different FDs, ranging from 1.9 for urban areas to 1.4 for rural ones. If all consumers were located along a single line, the FD of this layout would be equal to 1 (minimum value), while if the consumers fill the space uniformly, the FD would be 2 (maximum value). Clearly, in an urban situation (a) the consumers are distributed almost evenly across the area, while in a rural situation (d) consumers grouped into distinct clusters, with significant parts of the area that are empty.

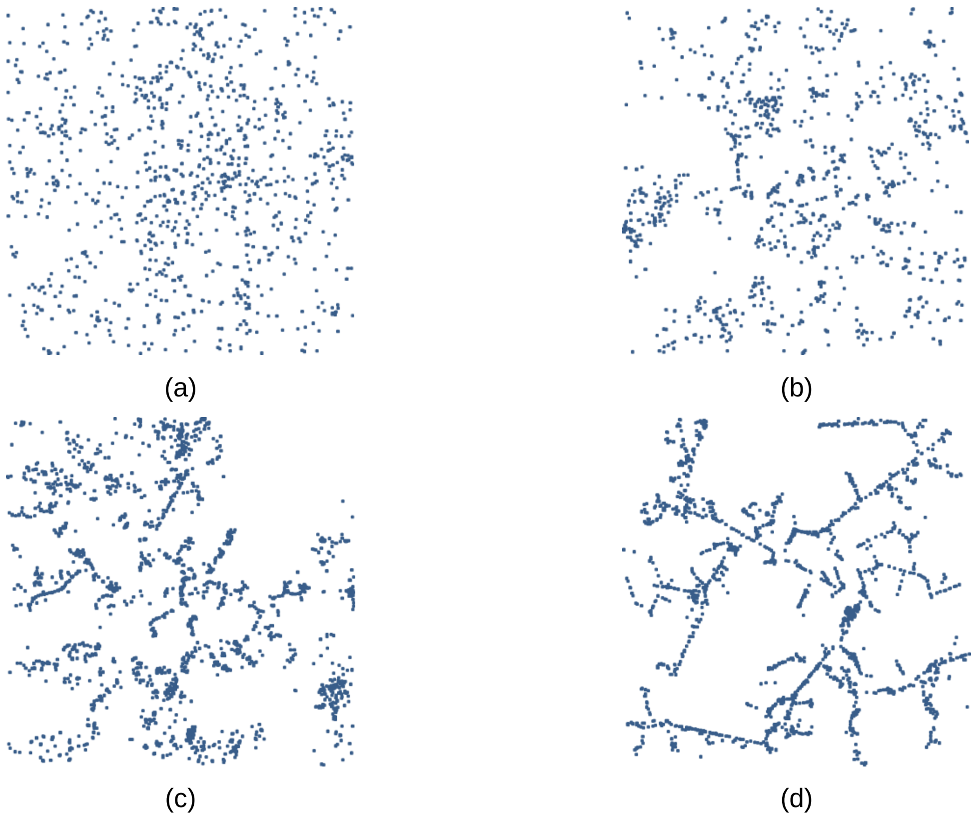


Figure A2.1 Examples of generated consumer layouts: (a) urban area (FD = 1.9); b) semi-urban area (FD = 1.75); c) semi-rural area (FD = 1.55); and d) rural area (FD = 1.4)

Given that the network layout generation is governed by stochastic rather than deterministic principles, many topologically different but statistically similar layouts can be generated using our fractal model. This is illustrated in Figure A2.2, where four evidently different networks are generated using the same key parameters (consumer density, area covered and branching rate). Nevertheless, these networks are statistically similar as they are characterised by the same FD, same number of customers and the same network length.

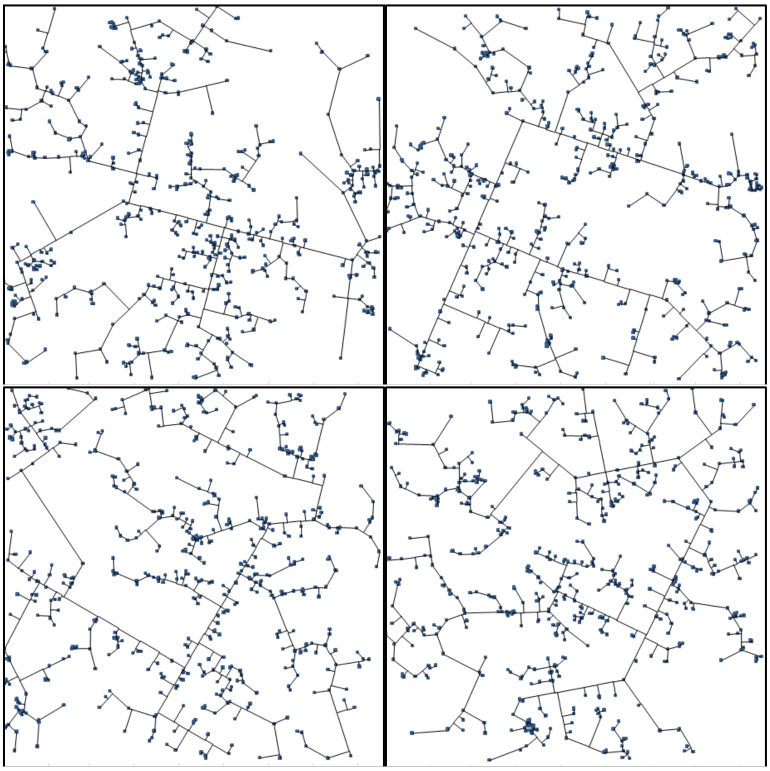


Figure A2.2 Example of four statistically similar LV networks

For a given actual consumer layout (consumer density), determined by the particular fractal dimension, many statistically similar networks can be generated (as shown in Figure A2.2). The obtained network lengths for these layouts are shown in Figure A2.3, which suggests a very strong correlation between different consumer patterns (characterised by the appropriate FD) and the network length density. The error bars in the figure indicate the minimum and maximum network density values obtained in a large number of model runs.

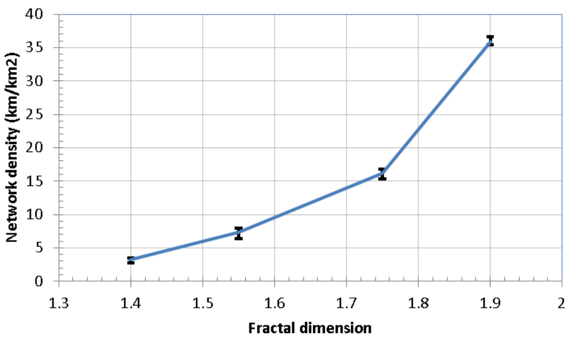


Figure A2.3 Relationship between length density of LV network and FD

The functional relationship between the network length density (total length of LV cables and lines per square kilometre) and the total LV network cost is illustrated in Figure A2.4, suggesting an almost linear relationship. In other words, network length density represents a key driver for the LV network cost, which also applies for the cost of reinforcing existing LV networks.

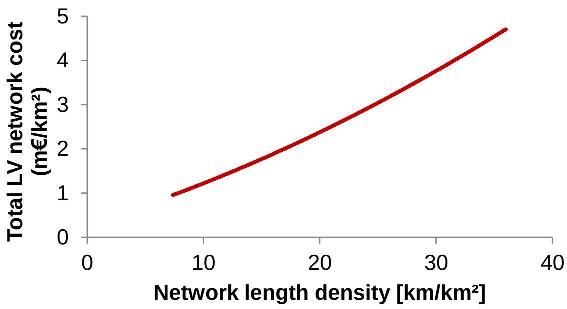
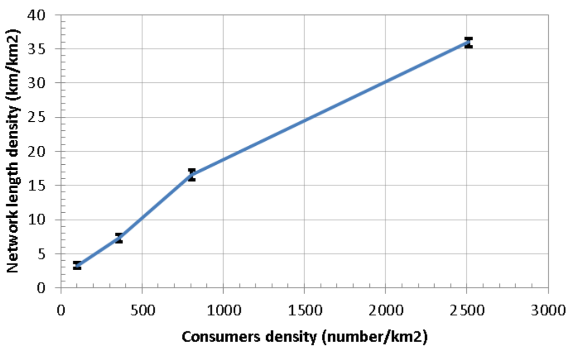
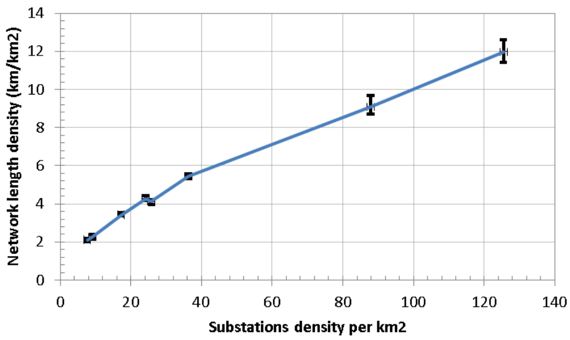


Figure A2.4 Total LV network cost as function of length density

Given the observed correlation between the FD and consumer density (Figure A2.3), it is possible to establish the correlation between consumer density and network length density illustrated in Figure A2.5a (the error bars show the minimum and maximum values observed). Our analysis has further revealed that similar to the close correlation between the LV network length density and consumer density, there is also a strong link between the HV network length density and the distribution substation density, as illustrated in Figure A2.5b. This demonstrates that HV distribution network lengths can be reasonably well estimated from the number of distribution substations (the estimation is more accurate for rural areas where the number of substations is higher). These correlations suggest that if realistic networks with actual consumer i.e. substation density could be generated, they would be representative of actual networks in terms of network length density, and consequently in terms of total network cost.



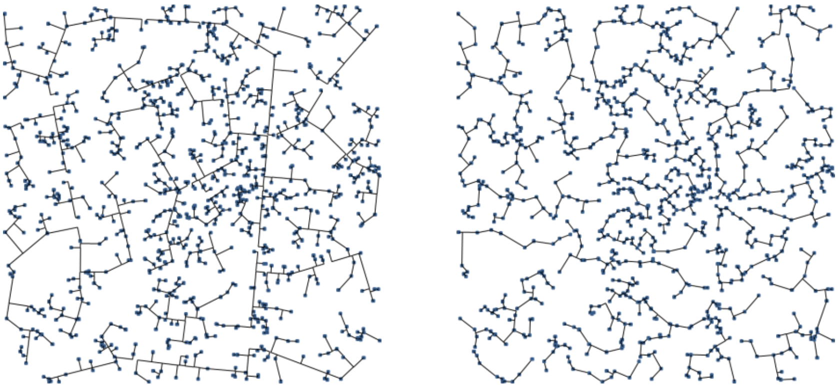
(a) LV network



(b) HV network

Figure A2.5 Correlation between network length density and: (a) consumer density in LV networks; (b) substation density in HV networks

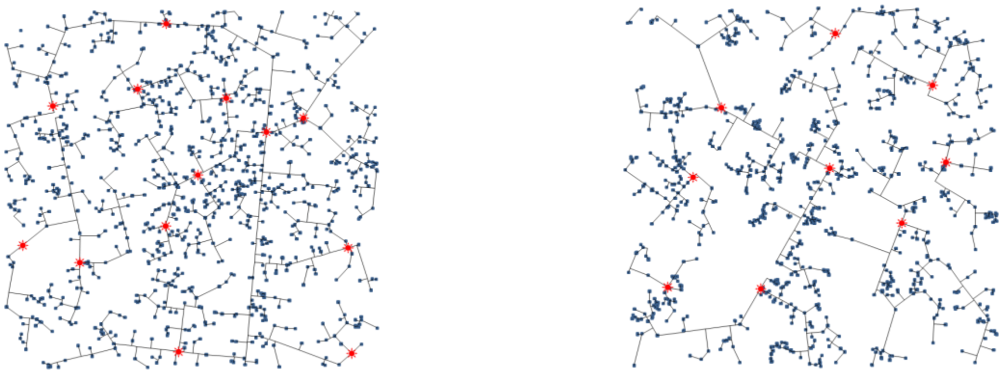
Figure A2.6 illustrates the impact of the assumed branching rate for the same consumer density i.e. the same distribution of consumers within a given area. Despite the same consumer layout, the resulting network topologies are visibly different – the network layout on the left has frequent branch splitting, whereas the one on the right contains far fewer branching points.



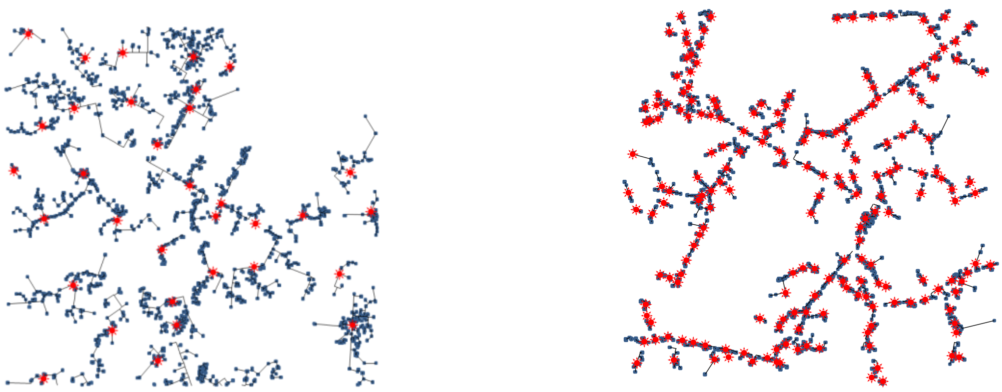
High branching rate *Low branching rate*

Figure A2.6 Impact of branching rate in LV networks

Examples of different network topologies that can be created by specifying the desired layout parameters are shown in Figure A2.7 for urban, rural and mixed areas, characterised by different consumer densities, areas and branching rates. In this procedure the parameters of representative networks are chosen to calibrate them against the actual distribution networks of the analysed system [24].



a) Urban area b) Semi-urban area



c) Semi-rural area d) Rural area

Note: Blue dots represent consumers, red stars represent distribution substations.

Figure A2.7 Different examples of consumer layouts generated using the fractal model

Mapping representative distribution networks to European statistical data

As mentioned earlier, European distribution networks are characterised by different planning and design standards. Moreover, for most countries there is very limited information publicly available on the actual design of existing networks, which could potentially support a highly detailed analysis. To cope with these issues, we have used a combination of statistical analysis of the distribution supply areas in each Member State on one hand, and the application of representative networks in the Fractal Model on the other.

The overall approach can be summarised as follows:

- In a first step, we collected information on population density and land use for close to 100,000 administrative units (municipalities, districts, provinces etc.)[23] in the EU-27.
- In a second step, the administrative areas were clustered into different population classes in each country, and mapped against a limited number of representative networks.
- In a third step, the design parameters of the representative networks in a given country were adjusted such that the sum of the individual networks corresponds to the overall size and structure of the distribution networks in that country.
- Finally, we assigned a set of generation and load profiles to different network classes, based on the assumed load and penetration of decentralised generation in each country.

As mentioned above, the first two steps were based on a comprehensive data set for close to 100,000 administrative units in the EU-27.[24] The administrative areas in a given country were then grouped into different density classes, which can be associated with different types of distribution networks. For illustration, Table A2.1 shows an example from Germany. The table shows how some 11,000 municipalities in four German regions used in the study are grouped into five different density classes. Unsurprisingly, the table suggests there are major differences between regions, with a large share of scarcely populated areas in Northern Germany, and more densely populated areas in the areas in the South (DE_S) and West (DE_W). Consequently, the share of rural and semi-rural areas is much higher in the first two regions (DE_NE and DE_NW), whilst the other two include a much higher share of urban and semi-urban areas.[25]

[23] The level of detail varies by country, subject to the quality of publicly available data.
[24] The corresponding data has been collected from Eurostat, national statistical offices and other sources.
[25] Please note that the individual administrative units cannot be directly equated to different networks. In fact, most administrative units cover different types of distribution supply areas themselves. For instance, in rural areas there will typically be smaller parts of the network with a higher population density. Similarly, even larger towns will usually comprise of some areas with much lower load density, such as in parks or the areas outside the inner city.

Table A2.1 Example of mapping of local areas to density classes for Germany

Density class (people/km^2)	DE_NE	DE_NW	DE_W	DE_S
Number of regions				
< 50	1,269	699	537	255
50-100	793	681	732	1,024
100-250	535	636	1,008	1,065
250-1000	209	415	460	712
> 1000	20	93	48	101
Total	**2,826**	**2,524**	**2,785**	**3,157**
Aggregate area (km^2)				
< 50	50,812	15,242	5,300	11,354
50-100	26,748	21,563	10,182	36,755
100-250	19,892	32,108	16,381	33,789
250-1000	8,662	20,811	9,418	18,214
> 1000	2,490	7,611	2,043	3,647
Total	**108,604**	**97,335**	**43,324**	**103,760**
Aggregate population				
< 50	1,501,556	506,620	188,557	433,683
50-100	1,889,187	1,590,516	748,545	2,740,615
100-250	3,066,271	5,137,881	2,656,371	5,239,721
250-1000	4,153,253	9,874,573	4,515,818	8,140,647
> 1000	5,715,566	13,771,151	3,143,161	6,737,910
Total	**16,325,833**	**30,880,741**	**11,252,452**	**23,292,576**

Using the number of different network classes and assumptions on their typical design (such as network length, number of connections or installed transformation capacity per km^2), we have then derived an estimate of the overall distribution infrastructure in a given country. This information was then compared against available evidence from each country, in order to calibrate the resulting assumptions.

Using the network classes developed as described, the main part of the distribution analysis is focused on quantifying the necessary network reinforcement costs. This analysis is based on the use of statistically representative models described earlier and derives an estimate of the required measures and cost for each of the different network classes. By aggregating the reinforcement costs across all network classes, it is possible to determine with very good accuracy the total distribution reinforcement costs in a given country for a given scenario characterised by EV deployment level and charging control approach (see Figure A2.8).

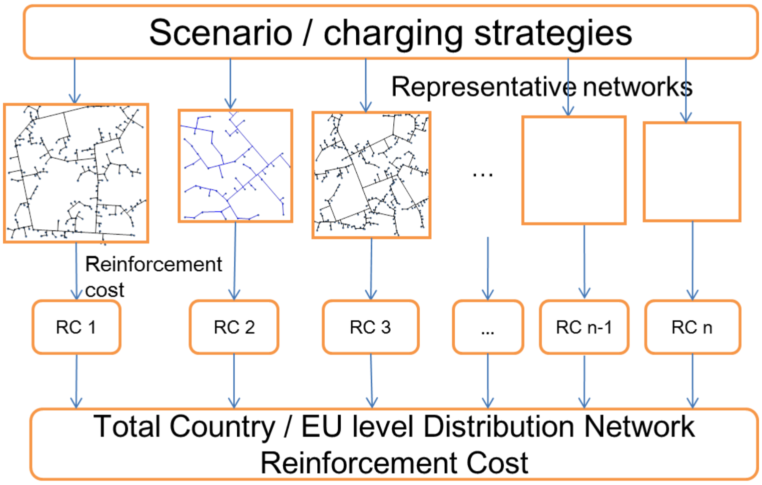


Figure A2.8 Estimating distribution reinforcement cost for a given scenario

Validation of network mapping

The mapping of representative networks to actual statistical information in various European countries and regions is carried out in such a way as to minimise deviations in terms of:

- Regional area
- Regional number of domestic consumers
- Country's distribution network statistics:
    - Network length (overhead lines, cables and total)
    - Number of substations/transformers (GMTs, PMTs and total)

The mapping process and the illustration of the accuracy are shown for the example of Spain. For the purpose of the analysis Spain is divided into five regions: North (ES_N), Northeast (ES_NE), Central (ES_C), Southeast (ES_SE) and South (ES_S). Spanish distribution network are approximated using ten representative networks: 4 rural, 3 intermediate and 3 urban networks. The parameters of these networks are given in Table A2.2.

Table A2.2 Representative distribution networks for Spain

Network type	Area (km^2)	Consumer density ($consumers/km^2$)	Substation density (DT/km^2)
Rural 1	400	5	0.35
Rural 2	80	25	1
Rural 3	40	50	1.5
Rural 4	20	100	2
Intermediate 1	12.5	200	2
Intermediate 2	6.3	400	3.2
Intermediate 3	4.9	800	2
Urban 1	2.4	1,600	3.3
Urban 2	1.7	3,200	7.7
Urban 3	0.8	6,400	11.9

In order to maximise mapping accuracy, each density class within each of the five regions is represented by a portfolio of representative models, i.e. by a certain number of each of the ten representative networks. Table A2.3 shows the comparison of actual statistical data with those approximated using the representative network. The comparison is made with respect to the number of domestic customers, geographical area, total length of the LV network and the total number of distribution transformers. Given that the data on network length and number of transformers is not available for individual regions and density classes, the comparison is only made with the aggregate national values.

The comparison confirms that it is possible to obtain a very close match with national statistical data by using representative distribution networks. In this case, the discrepancy in terms of total area is about –1%, while the deviation in total number of domestic consumers is only about 0.2%. The approximation of key network parameters is also very accurate – the difference is 0.34% for the total network length, and 0.15% for the number of distribution transformers. Given the high level of uncertainty around forecasting the demand, EV penetration, generation capacity evolution etc. in the 2030 horizon, this level of accuracy appears to be more than acceptable.

Similar levels of accuracy are obtained using the same approach to representative network mapping for Italy (Table A2.4), Germany (Table A2.5), Denmark and Ireland (Table A2.6) and Great Britain (Table A2.7).

Table A2.3 Accuracy of representative network mapping for Spain

	Statistical data					Representative network data					Discrepancies				
Density class (people/km^2)	**ES_N**	**ES_NE**	**ES_C**	**ES_SE**	**ES_S**	**ES_N**	**ES_NE**	**ES_C**	**ES_SE**	**ES_S**	**ES_N**	**ES_NE**	**ES_C**	**ES_SE**	**ES_S**
Area (km^2)															
< 50	85,593	69,880	144,535	33,123	51,363	85,616	67,225	141,901	33,129	51,386	0.03%	-3.80%	-1.82%	0.02%	0.04%
50-100	14,304	5,422	9,876	4,095	15,360	14,304	5,433	9,877	4,096	15,363	0.00%	0.20%	0.01%	0.02%	0.02%
100-250	8,606	4,364	5,626	4,039	5,633	8,607	4,371	5,625	4,040	5,634	0.01%	0.16%	-0.01%	0.02%	0.02%
250-1000	7,686	3,955	2,038	4,508	5,349	7,693	3,966	2,038	4,513	5,335	0.10%	0.27%	0.02%	0.12%	-0.27%
> 1000	2,895	1,470	279	1,179	1,099	2,890	1,470	278	1,178	1,098	-0.18%	0.03%	-0.18%	-0.08%	-0.08%
Total	**119,083**	**85,091**	**162,353**	**46,943**	**78,804**	**119,109**	**82,464**	**159,719**	**46,955**	**78,815**	**0.02%**	**-3.09%**	**-1.62%**	**0.03%**	**0.01%**
Number of domestic consumers															
< 50	519,697	302,079	659,224	213,915	418,768	519,776	319,653	674,739	213,950	418,832	0.02%	5.82%	2.35%	0.02%	0.02%
50-100	384,153	152,026	247,898	117,056	436,544	384,211	152,020	247,903	117,086	436,606	0.02%	0.00%	0.00%	0.03%	0.01%
100-250	542,186	264,432	315,107	268,632	359,632	542,192	264,407	315,090	268,632	359,620	0.00%	-0.01%	-0.01%	0.00%	0.00%
250-1000	1,407,186	840,776	291,676	848,580	824,042	1,405,925	838,980	291,364	847,726	826,819	-0.09%	-0.21%	-0.11%	-0.10%	0.34%
> 1000	3,541,561	2,223,452	213,068	1,035,395	1,032,535	3,547,610	2,221,531	211,311	1,036,406	1,033,104	0.17%	-0.09%	-0.82%	0.10%	0.06%
Total	**6,394,782**	**3,782,764**	**1,726,973**	**2,483,579**	**3,071,520**	**6,399,713**	**3,796,591**	**1,740,407**	**2,483,799**	**3,074,982**	**0.08%**	**0.37%**	**0.78%**	**0.01%**	**0.11%**
LV network length (km)															
Overhead	402,774					403,703					0.23%				
Cable	62,449					63,117					1.07%				
Total	**465,223**					**466,820**					**0.34%**				
Number of distribution transformers															
DT	**307,936**					**308,401**					**0.15%**				

Table A2.4 Accuracy of representative network mapping for Italy

	Statistical data			Representative network data			Discrepancies		
Density class (people/km²)	**IT_N**	**IT_M**	**IT_S**	**IT_N**	**IT_M**	**IT_S**	**IT_N**	**IT_M**	**IT_S**
Area (km²)									
< 50	26,550	43,588	24,327	26,549	43,622	24,362	0.00%	0.08%	0.14%
50-100	11,619	21,419	21,255	11,619	21,426	21,279	-0.01%	0.03%	0.12%
100-250	14,871	18,816	22,624	14,870	18,823	22,650	-0.01%	0.04%	0.12%
250-1000	11,747	11,501	12,882	11,741	11,248	12,360	-0.05%	-2.20%	-4.05%
> 1000	1,763	2,347	2,647	1,763	2,346	2,648	-0.01%	0.00%	0.01%
Total	**66,551**	**97,670**	**83,735**	**66,542**	**97,465**	**83,299**	**-0.01%**	**-0.21%**	**-0.52%**
Number of domestic consumers									
< 50	212,643	439,105	300,370	212,627	438,861	300,208	-0.01%	-0.06%	-0.05%
50-100	334,784	604,082	623,962	334,761	603,682	623,368	-0.01%	-0.07%	-0.10%
100-250	957,612	1,175,122	1,414,591	957,498	1,173,563	1,411,592	-0.01%	-0.13%	-0.21%
250-1000	2,168,326	2,000,699	2,164,468	2,168,247	2,039,035	2,240,596	0.00%	1.92%	3.52%
> 1000	1,451,029	1,830,912	2,508,518	1,451,017	1,827,757	2,500,149	0.00%	-0.17%	-0.33%
Total	**5,124,394**	**6,049,920**	**7,011,909**	**5,124,150**	**6,082,897**	**7,075,913**	**0.00%**	**0.55%**	**0.91%**
LV network									
Length (km)		892,220			890,223			-0.22%	
No. of DTs		501,834			501,094			-0.15%	

Table A2.5 Accuracy of representative network mapping for Germany

	Statistical data				Representative network data				Discrepancies			
Density class (people/km^2)	**DE_NE**	**DE_NW**	**DE_W**	**DE_S**	**DE_NE**	**DE_NW**	**DE_W**	**DE_S**	**DE_NE**	**DE_NW**	**DE_W**	**DE_S**
Area (km^2)												
< 50	50,812	15,242	5,300	11,354	50,801	15,247	5,306	11,359	-0.02%	0.03%	0.11%	0.04%
50-100	26,748	21,563	10,182	36,755	26,756	21,571	10,190	36,805	0.03%	0.04%	0.08%	0.14%
100-250	19,892	32,108	16,381	33,789	19,888	32,129	16,406	33,848	-0.02%	0.07%	0.15%	0.18%
250-1000	8,662	20,811	9,418	18,214	8,658	20,721	9,405	17,549	-0.04%	-0.43%	-0.13%	-3.65%
> 1000	2,490	7,611	2,043	3,647	2,398	7,593	1,852	3,658	-3.71%	-0.24%	-9.33%	0.30%
Total	**108,604**	**97,335**	**43,324**	**103,760**	**108,500**	**97,261**	**43,160**	**103,219**	**-0.09%**	**-0.08%**	**-0.38%**	**-0.52%**
Number of domestic consumers												
< 50	600,622	202,648	75,423	173,473	600,198	202,551	75,414	173,415	-0.07%	-0.05%	-0.01%	-0.03%
50-100	755,675	636,206	299,418	1,096,246	754,484	635,590	299,069	1,094,910	-0.16%	-0.10%	-0.12%	-0.12%
100-250	1,226,508	2,055,152	1,062,548	2,095,888	1,223,392	2,051,358	1,058,305	2,088,509	-0.25%	-0.18%	-0.40%	-0.35%
250-1000	1,661,301	3,949,829	1,806,327	3,256,259	1,656,265	3,958,155	1,798,147	3,331,023	-0.30%	0.21%	-0.45%	2.30%
> 1000	2,286,226	5,508,460	1,257,264	2,695,164	2,333,158	5,520,945	1,343,562	2,689,322	2.05%	0.23%	6.86%	-0.22%
Total	**6,530,333**	**12,352,296**	**4,500,981**	**9,317,030**	**6,567,498**	**12,368,599**	**4,574,496**	**9,377,180**	**0.57%**	**0.13%**	**1.63%**	**0.65%**
LV network length (km)												
Total	1,164,012				1,189,631				2.20%			

Table A2.6 Accuracy of representative network mapping for Denmark and Ireland[26]

	Statistical data			**Representative network data**			**Discrepancies**		
Density class (people/km^2)	**DK_W**	**DK_E**	**IE**	**DK_W**	**DK_E**	**IE**	**DK_W**	**DK_E**	**IE**
Area (km^2)									
< 50	8,879	0		8,956	0		0.87%	0.00%	
50-100	15,518	4,882		15,858	4,888		2.19%	0.13%	
100-250	7,826	3,353		7,948	3,354		1.55%	0.05%	
250-1000	907	1,209		912	1,216		0.54%	0.56%	
> 1000	0	320		0	321		0.00%	0.27%	
Total	**33,131**	**9,764**	**84,116**	**33,674**	**9,780**	**84,481**	**1.64%**	**0.16%**	**0.43%**
Number of domestic consumers									
< 50	145,538	0		147,020	0		1.02%	0.00%	
50-100	424,238	145,050		429,863	146,444		1.33%	0.96%	
100-250	426,839	191,267		429,658	192,272		0.66%	0.53%	
250-1000	222,289	236,535		223,108	237,647		0.37%	0.47%	
> 1000	0	439,884		0	439,552		0.00%	-0.08%	
Total	**1,218,904**	**1,012,736**	**2,531,269**	**1,229,649**	**1,015,916**	**2,532,185**	**0.88%**	**0.31%**	**0.04%**
LV network length (km)									
Overhead	7,112		79,990	7,102		79,608	-0.13%		-0.48%
Cable	87,343		16,951	87,735		16,962	0.45%		0.07%
Total	**94,455**		**96,940**	**94,837**		**96,569**	**0.40%**		**-0.38%**
Number of distribution transformers									
PMT			320,982			321,529			0.17%
GMT			12,239			12,231			-0.06%
Total			**333,221**			**333,760**			**0.16%**

[26] Ireland here refers to both the Republic of Ireland and Northern Ireland. Some values have been estimated due to lack of available data.

Table A2.7 Accuracy of representative network mapping for Great Britain

	Statistical data						Representative network data						Discrepancies
	GB_SCO	**GB_N**	**GB_M**	**GB_LON**	**GB_S**	**Total GB**	**GB_SCO**	**GB_N**	**GB_M**	**GB_LON**	**GB_S**	**Total GB**	**Total GB**
Number of domestic consumers													
Total	2,996,192	7,656,576	5,047,743	2,311,841	11,403,761	**29,416,113**	2,996,194	7,656,574	5,047,738	2,310,478	11,403,759	**29,416,238**	**0.0%**
LV network length (km)													
Overhead	8,552	12,160	10,896	0	33,321	**64,929**	8,552	12,160	10,896	0	33,321	**64,929**	0.0%
Cable	36,192	89,863	59,570	22,556	119,428	**327,609**	36,192	89,863	59,570	22,558	119,428	**327,598**	0.0%
Total	**44,744**	**102,023**	**70,466**	**22,556**	**152,749**	**392,538**	**44,744**	**102,023**	**70,466**	**22,558**	**152,749**	**392,527**	**0.0%**
Number of distribution transformers													
PMT	67,823	68,388	57,706	0	149,940	**343,857**	67,823	68,388	57,706	0	149,940	**343,857**	0.0%
GMT	26,175	50,448	35,058	17,145	101,639	**230,465**	26,175	50,448	35,058	17,143	101,639	**230,474**	0.0%
Total	**93,998**	**118,836**	**92,764**	**17,145**	**251,579**	**574,322**	**93,998**	**118,836**	**92,764**	**17,143**	**251,579**	**574,331**	**0.0%**

Quantifying the network reinforcement cost characteristic

As mentioned earlier, the key purpose of developing the representative network approach is to characterise that could be included in the same assessment framework as considerations associated with system operation and generation and transmission capacity.

As part of its work on Deliverable 4.3-C1 of Green eMotion, Imperial College London has developed ITRES, a tool for calculating the necessary reinforcement of LV distribution networks driven by EV integration. This tool was used in Deliverable 4.3-B2 to analyse the potential reinforcement requirements of several specific LV networks in Denmark, Italy and Spain. This analysis has however been constrained to the analysed networks only, and did not allow for drawing any system-level conclusions on reinforcement requirements in entire countries or regions. It also did not consider the specifics of other segments of the electricity supply system, such as generation or transmission.

Deliverable 4.3-B3 (also prepared by Imperial), which discusses the functional requirements for future distribution planning tools, argues that in order to achieve efficient operation and planning from the whole-system perspective, future network planning tools will have to be able to include the interaction with other segments in the electricity supply chain [25]. This is particularly relevant to the objective to ensure an efficient integration of output supplied by intermittent renewable generation.

Flexible EV demand can be used not only to reduce peak loads and consequently improve network capacity utilisation, but also to respond to opportunities in the energy, reserve and ancillary services markets. EV charging could be optimised to maximise the commercial benefits when exposed to time-varying energy prices, which would entail shifting significant demand volumes to periods with abundant renewable generation output (e.g. wind or solar) and therefore lower electricity prices. In a hypothetical future situation where high wind and/or solar generation output coincides with system peak demand, much of EV charging incentivised by low prices would be shifted towards the time around system peak to make full use of available wind energy. With a large number of EVs being charged during peak hours (driven by supply price signals) the stress on the distribution networks may become significant, resulting in a much higher proportion of overloaded feeders and transformers (and hence higher reinforcement cost) than in the case where EV charging is controlled with the objective to support the local distribution network. This simple example illustrates that the independent “unconstrained” operation of the electricity market without due consideration of distribution network limitations will potentially be suboptimal in terms of the overall efficiency of the end-to-end electricity delivery chain.

The challenge for distribution planning is therefore to enable a coordinated assessment of both supply and network businesses in order to avoid conflicts between local management and national system conditions. Of particular relevance for flexible EV demand is the capability to e.g. provide ancillary services or participate in V2G schemes to support the wider system, which may create both conflicts and synergies with respect to the requirements of the local distribution network.

The whole-system modelling approach presented in this report is therefore used to illustrate the impact of large-scale EV uptake on European electricity system by including both network and supply considerations in system analysis, i.e. by finding optimal trade-offs between supporting different segments of the system. This is facilitated by introducing into the DSIM model formulation (described in Chapter 0) the peak demand vs. reinforcement cost characteristics obtained for each of the representative networks in each country or region. Examples of such cost characteristics for several representative networks are provided in Figure A2.9 (the figure distinguishes between LV and MV network reinforcement cost).

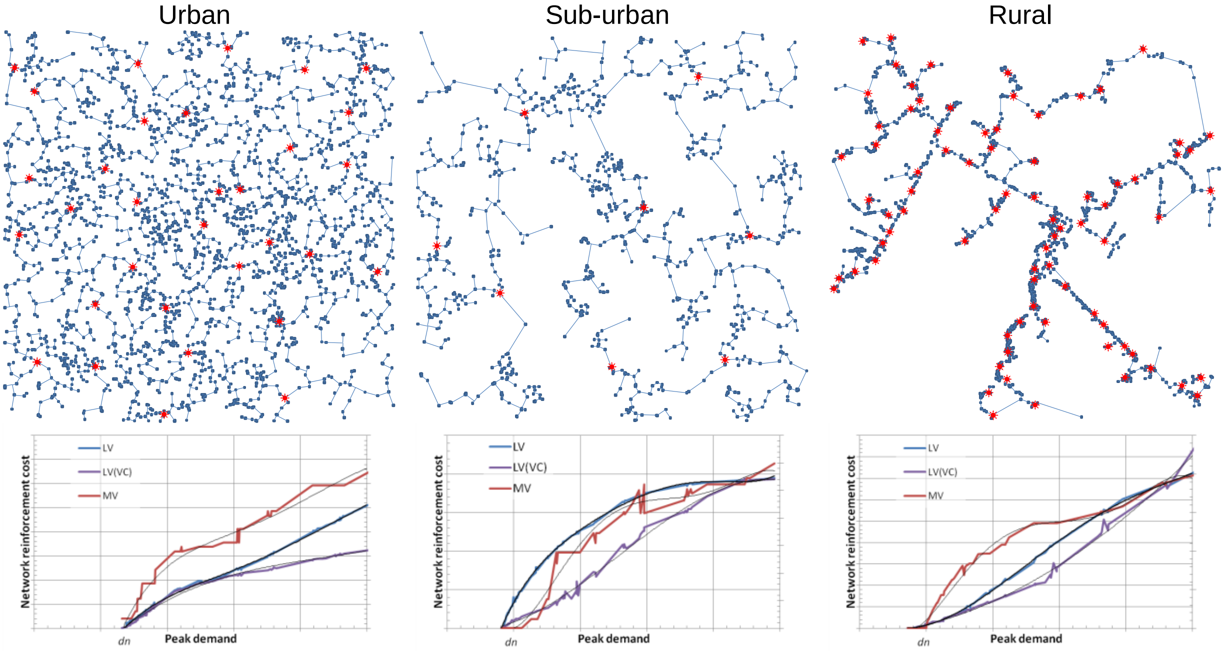


Figure A2.9 Examples of network reinforcement cost characteristics

This enables our model to identify optimal trade-offs between different objectives pursued by flexible EV charging demand. In other words, the flexible EV demand is shifted by the model in such a way that the total cost savings from avoided investments in distribution, transmission and generation capacity, as well as from more efficient system operation, are maximised. These trade-offs could not be adequately quantified in a framework which considers each of these different segments separately.

As discussed earlier, using statistically representative networks at the level of entire countries provides very accurate estimates of reinforcement costs due to EV deployment. This is enabled by replicating in representative networks those statistical properties of actual networks that are the key drivers for network reinforcement: network length and consumer density. The approach presented here therefore enables us to quantify the distribution reinforcement cost driven by EVs very efficiently and provide it as in input into our optimisation model along simultaneously with the cost of generation and transmission capacity and the cost of system operation.