INTEGRATION OF ELECTRIC VEHICLES INTO DISTRIBUTION NETWORKS

A THESIS SUBMITTED TO CARDIFF UNIVERSITY
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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ABSTRACT

The objectives of this research were to investigate the impact of electric vehicle battery charging on grid demand at a national level and on the steady state parameters of distribution networks. An agent-based control system that coordinates the battery charging of electric vehicles according to electric vehicle owner preferences, distribution network technical limits and electricity prices was designed and developed and its operation was tested experimentally.

The impact on grid demand peak increases at the national systems of Great Britain and Spain was evaluated using low and high electric vehicle uptake levels of 7% and 48.5% of the car fleet for the year 2030 with a deterministic method. It was found that a low uptake will not raise significantly the grid demand peaks in both countries under investigation. However, a high uptake will raise significantly the grid demand peaks.

The impact from residential electric vehicle battery charging on steady state voltages, power line losses, transformers' and cables' loadings of distribution networks was evaluated using a deterministic and a probabilistic method. It was found that low and medium uptake levels of electric vehicles equivalent to 12.5% and 33% per residential area of 384 customers in 2030, can be safely accommodated by reinforcing the distribution network. A combination of reinforcements, installation of micro-generators and control of electric vehicle battery charging will be required to accommodate safely a high uptake of 71% with regards to the constraints studied.

An agent-based control system that coordinates the battery charging of electric vehicles was designed and developed. Search techniques and neural networks were used for the decision making processes. The ability of the agent-based control system to operate successfully in both normal and abnormal conditions for the electrical network was proved with experimental validation in the laboratory of Tecnalia research institute in Spain.

DECLARATION

This work has not been submitted in substance for any other degree or award at this or any other university or place of learning, nor is being submitted concurrently in candidature for any degree or other award.

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This thesis is being submitted in partial fulfilment of the requirements for the degree of PhD.

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This thesis is the result of my own independent work/investigation, except where otherwise stated. Other sources are acknowledged by explicit references. The views expressed are my own.

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LIST OF PUBLICATIONS

The following papers have been accepted for publication or published based on work done for this thesis, work done within the framework of the doctorate degree, or collaboration with other researchers.

JOURNAL PAPERS

1. Papadopoulos, P., Akizu, O., Cipcigan, L. M., Jenkins, N., and Zabala, E., "Electricity demand with electric cars in 2030: comparing Great Britain and Spain", Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy, June 27, 2011, 0957650911406343.

2. Papadopoulos, P., Skarvelis-Kazakos, S., Grau, I., Cipcigan, L. M. and Jenkins N., "GB study on electric vehicles in distribution networks", Institute of Engineering and Technology, Electrical Systems in Transportation, 2011, [Accepted for publication].

BOOK CHAPTER

3. Grau Unda, I., Papadopoulos P., Skarvelis-Kazakos S., Cipcigan L. M., and Jenkins N., "Energy storage for balancing a local distribution network area", Chapter in Energy Storage in the Emerging Era of Smart Grids, InTech, 2011. ISBN 978-953-307-269-2.

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distributed generation", IEEE Vehicle Power and Propulsion Conference, Lille, France, 2010.

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STANDARDS DEVELOPMENT AND PROJECT PARTICIPATION

Within the framework of the doctorate degree, the author participated in the following projects and standards development:

1. **IEEE P2030.1^{TM} Guide for Electric-Sourced Transportation Infrastructure -** Task Force 2: Grid Impact – Member/co-author
2. **EU FP7 Project Distributed Energy Resources Research Infrastructures (DERri) -** *EU Project Contract Number: 228449.*

   Lead User of DERri project: "Electric Vehicle Operated Low Voltage Electricity networks with Multi-Agent Systems (EVOLVE-MAS)".
3. **EU FP7 Project Mobile Energy Resources in Grids of Electricity (MERGE) -** *EU Project Contract No: 241399*, co-author in**:**
   - *Deliverable 1.2* Extend Concepts of MG by Identifying Several EV Smart Control Approaches to be embedded in the Smart Grid Concept to manage EV individually or in Clusters.
   - *Deliverable 1.3* Controls and EV Aggregation for Virtual Power Plants.
   - *Deliverable 3.1* Scenarios for the evolution of generation system and transmission, distribution, grid evolution requirements for different scenarios of EV penetration in different countries.

NOMENCLATURE

LIST OF ABBREVIATIONS

AC	Alternate Current
ACC	Agent Communication Channel
ACL	Agent Communication Language
ADDRESS	Active Distribution networks with full integration of Demand and distributed energy Resources
AI	Artificial Intelligence
AID	Agent Identifier
ANM	Active Network Management
ANN	Artificial Neural Network
ANSI	American National Standards Institute
AP	Agent Platform
ARCHON™	ARchitecture for Cooperative Heterogeneous ONline Systems
BERR	Department for Business, Enterprise and Regulatory Reform
BMW	Bayerische Motoren Werken
BEV	Battery Electric Vehicle
CO_2	Carbon Dioxide
CEN	Comité Européen de Normalisation
CENELEC	Comité Européen de Normalisation Électrotechnique
CORBA	Common Object Request Broker Architecture
CSDER	Communication Software for Distributed Energy Resources

DCC	Distribution Control Centre
DECC	Department of Energy and Climate Change
DER	Distributed Energy Resource
DERri	Distributed Energy Resources Research Infrastructures
DF	Directory Facilitator
DfT	Department for Transport
DG	Distributed Generation
DGTREN	Directorate-General for Energy and Transport
DMS	Distribution Management System
DNO	Distribution Network Operator
DoD	Depth of Discharge
DSM	Demand Side Management
DSO	Distribution System Operator
DSSM	Distribution Systems Simulation Model
EMF	Electro-Magnetic Fields
EMS	Energy Management System
ENA	Energy Networks Association
ESPC	Energy Service Provider Company
ESCO	Energy Service Companies
ETSI	European Telecommunications Standards Institute
EU	European Union
EU-DEEP	European project birth of a European Distributed Energy Partnership
EV	Electric Vehicle
EVS/A	Electric Vehicle Supplier/Aggregator
FCV	Fuel Cell Vehicles
FIPA	Foundation of Intelligent and Physical Agents

GB	Great Britain
GSP	Grid Supply Point
HEV	Hybrid Electric Vehicle
HPR	Heat to Power Ratio
HV	High Voltage
IBM	International Business Machines
ICE	Internal Combustion Engine
IEC	International Electrotechnical Commission
IED	Intelligent Electronic Device
IEEE	Institute of Electrical and Electronic Engineers
IET	Institution of Engineering and Technology
IP	Interaction Protocol
LA	Local Aggregator
LBC	Load Banks Controller
LV	Low Voltage
MAPE	Mean Absolute Percentage Error
MAS	Multi-Agent Systems
MATSIM	Multi-Agent Transport Simulation
MC	Monte Carlo
mCHP	micro Combined Heat and Power
MDP	Markov Decision Process
mGen	micro-Generation
MERGE	Mobile Energy Resources in Grids of Electricity
MLP	Multi-Layer Perceptron
MSE	Mean Square Error
MTP	Message Transport Protocol

MTS	Message Transport System
MV	Medium Voltage
NTUA	National Technical University of Athens
OFGEM	Office for Gas and Electricity Markets
PDCIM	Distribution Circuit Impact Model
PEDA	Protection Engineering Diagnostic Agents
PHEV	Plug-in Hybrid Electric Vehicle
RA	Regional Aggregator
RPROP	Resilient propagation
RIIO	Revenue set to deliver strong Incentives, Innovation and Outputs
RTU	Remote Terminal Units
SAE	Standards Association of Automotive Engineers
SC	Smart Charging
SCS	Substation Control Systems
SCADA	Supervisory Control and Data Acquisition Systems
SOA	Service Oriented Architectures
SoC	State of Charge
TCOPF	Time Coordinated Optimal Power Flow
TFT-LCD	Thin Film Transistor- Liquid Crystal Display
TSO	Transmission System Operator
UK	United Kingdom
UKERC	UK Energy Research Centre
US	United States
VPP	Virtual Power Plant
V2G	Vehicle to Grid
WT	Wind Turbines

XML	eXtensible Markup Language

LIST OF SYMBOLS AND UNITS

a	Constant
A	Ampere
a_{cd}	Average charge/discharge cycles of an EV battery per day
b	Branching factor
b_{ANN}	ANN bias term
C_B	Battery capacity (kWh)
c_B	Capital cost of the battery (£)
c_{BU}	Battery utilisation cost (£/kWh)
$c_{p,i}$	Cost of the node schedule for each node i,
d	Day index
d_r	Annual interest rate
e	Constant base of the natural logarithm
e_B	Average battery efficiency
e_C	Average efficiency of the EV charger
e_{Cn}	Efficiency of EV charger at 13A
E_x	Energy eXchange
$f(u_i)$	ANN activation function
gCO_2/km	Grams of Carbon Dioxide per kilometre
GBs	Gigabytes
h	Hour index
$I(t_e)$	Exponential decay of the modelled Lithium-ion battery after 90% SoC
kWh	Kilo-Watt-hour
l_y	Lifetime of the battery (years)

L_c	Lifetime of the battery (cycles)
L_{max}^{sim}	Maximum load demand (kW) of the feeder used in the case studies
L_{max}^{lab}	Maximum load of the load banks (kW)
N_d	Number of simulated days
N_f	Node factor
n_p	Number of charging schedules sent by each EV agent of each node
P	Active Power
p_c	Remaining number of hours of EV connection
P_C	Power rating of the EV charger (kW)
$P_{i,\,t}$	Power demand of all EVs connected to each node i for each time-step t,
P^{max}	Power limit of each node i and time-step t
Q	Reactive Power
R	Randomisation factor
R^2	Sum of squares of the residuals for a polynomial or exponential fit
R_f	Risk factor
Sd	Daily randomisation factor
Sh	Hourly randomisation factor
SoC_d	Desired SoC at the time of disconnection (kWh)
SoC_T	Estimated SoC of the next operational period (kWh)
t_c	Current point in time
t_e	Time when estimation is needed, during the exponential range of the battery charging characteristic
t_s	Time when estimation is needed during the stable range of the battery charging characteristic
T_d	Daily horizon with 24 hourly time-steps
TBs	Terabytes
V	Volt

W	Watt
w_n	ANN synaptic weights,
x_n	ANN input signals
Y_{ANN}	ANN output
Δ_{ij}	Updated value for the synaptic weights *i* to *j* for iteration *t*
$\Delta_{ij}^{(t-1)}$	Updated value for the synaptic weights *i* to *j* for iteration *t-1*
E	Training error of ANN
η	A factor where $0 < \eta^{-} < 1 < \eta^{+}$
$\frac{\theta E}{\theta w_{ij}}^{(t)}$	Gradient weight for the synaptic weights *i* to *j* for iteration *t*
$\frac{\theta E}{\theta w_{ij}}^{(t-1)}$	Gradient weight for the synaptic weights *i* to *j* for iteration *t-1*
μ	Laboratory load scaling factor

CHAPTER 1

INTRODUCTION

Socio-economic, environmental, technical and political factors are driving a transition of the transportation sector towards low carbon vehicles. The term low carbon vehicles refers to vehicles that release low Carbon Dioxide (CO_2) quantities during their operation. A significant share of European Union's (EU's) 27 member countries' CO_2 emissions (23.1%) is attributed to road transport [1]. Targets have been set by the EU with respect to the levels of CO_2 emissions from vehicles for the years 2015 and 2020 [2]. These targets together with the actual average CO_2 emission factors (gCO_2/km) per vehicle for the year 2010 are shown in Table 1.1.

The stimulus of the EU legislation and the associated penalties from exceeding certain CO_2 emission levels (in the United Kingdom (UK), the CO_2 road tax starts from £105 for new cars emitting more that 130g/km according to [3]), has encouraged major automotive manufacturers, to announce production of Electric Vehicles (EVs) (Table 1.2). These vehicles are anticipated to gain an important market share over conventional Internal Combustion Engine (ICE) powered vehicles. Analysis on lifecycle CO_2 emissions in document [4] that was published for the British government concludes that in the year 2030, EVs may be able to produce less than 50g/km CO_2 emissions, approximately one third of petrol based vehicles.

Table 1.1 Average actual (2010) and target (2015 and 2020) tailpipe CO_2 emissions for new vehicles [5]-[6]

Year	**UK (gCO_2/km)**	**EU_{27} (gCO_2/km)**
2010	144.2	140.3
Year	**EU_{27} (gCO_2/km)**	
2015	130	
2020	95	

Table 1.2 Major automotive manufacturers who have announced EV production

Manufacturer	**Source**
Bayerische Motoren Werken (BMW)	[7]
Daimler/Mercedes Benz	[8]
Fiat	[9]
Ford	[10]
General Motors/Chevrolet	[11]
Honda	[12]
Mazda	[13]
Mitsubishi	[14]
Nissan	[15]
Peugeot/Citroën	[16]
Renault	[16]
Suzuki	[18]
Toyota	[19]
Volkswagen Group	[20]
Volvo	[21]

There are mainly two technologies which are expected to penetrate the EV market in the forthcoming years according to [4]: Plug-in Hybrid EVs (PHEVs) and full EVs or Battery EVs (BEVs). Hybrid Electric Vehicles (HEVs) and Fuel Cell Vehicles (FCV) are also electric vehicles but since these technologies do not represent a load for the power system, they are not considered in this thesis. The term Electric Vehicles or EVs in this thesis refers to PHEVs and BEVs. PHEVs are equipped with an ICE in addition to their battery to provide traction or charge the battery, while BEV motors rely solely on the electrical energy stored in the battery. Both EV technologies will require charging infrastructure connected to the electrical networks to charge their batteries.

From a power system viewpoint, Electric Vehicles may be considered as:

i) Simple loads, drawing a continuous current from the electricity network.
ii) Flexible loads that may allow an aggregator company to interrupt or coordinate their charging procedure. Such a company could aggregate the demand of multiple EVs and enable their participation in electricity markets. The benefits of aggregation are referred in Section 1.3 and the different aggregator types that are currently found in the literature are defined in Section 2.3.1.

iii) Storage devices that may allow an aggregator company to interrupt or coordinate their charging procedure, or even request power injections from their batteries back to the grid. The latter is known as Vehicle to Grid (V2G) [22].

A unique characteristic of EVs in terms of power systems is that they are mobile devices expected to connect to various locations of electricity networks at different times of a day. It is inevitable that traditional power system planning and operation will face challenges.

1.1 TRADITIONAL POWER SYSTEM OPERATION

The Electricity Supply Industry in the UK comprises five functions [23]; Generation, Transmission, Distribution, Supply and Metering.

Large power plants generate bulk energy with the majority of it being currently produced in nuclear, gas and coal fired stations (91% of the net electricity supplied in the UK in 2010 [24]). The bulk generated energy is produced in 3-phase Alternate Current (AC) form and enters the national grid's transmission system at the Grid Supply Points (GSPs) through bulk supply transformers [25].

The transmission system of Great Britain (GB) transfers electricity in 400kV, 275kV and 132kV or lower voltages through 25,000 km of HV overhead lines [26] and 2,000 of underground HV lines, to large or special demand customers and to GSPs [23]. The GSPs are connection points to large power plants and entry points to the 14 distribution network areas operated by eight Distribution Network Operators (DNOs) [26].

Electricity distribution refers to the allotment of electricity to the majority of commercial, industrial and residential customers through a variety of voltage levels (66kV, 33kV, 22kV, 11kV, 6.6kV, 400V, 230V, and 132kV only in England and Wales) according to the demand [23].

Electricity supply companies are concerned with the marketing and billing of electricity. In the UK, there are currently over 18 energy companies [27]. These firms cooperate with licensed meter operators (that operate independently or they are DNO subsidiaries) who measure real time power flows in all levels of the electricity network [23] to ensure accurate billing. The conventional power system planning and operational paradigm follows the arrangement described in Fig. 1.1.

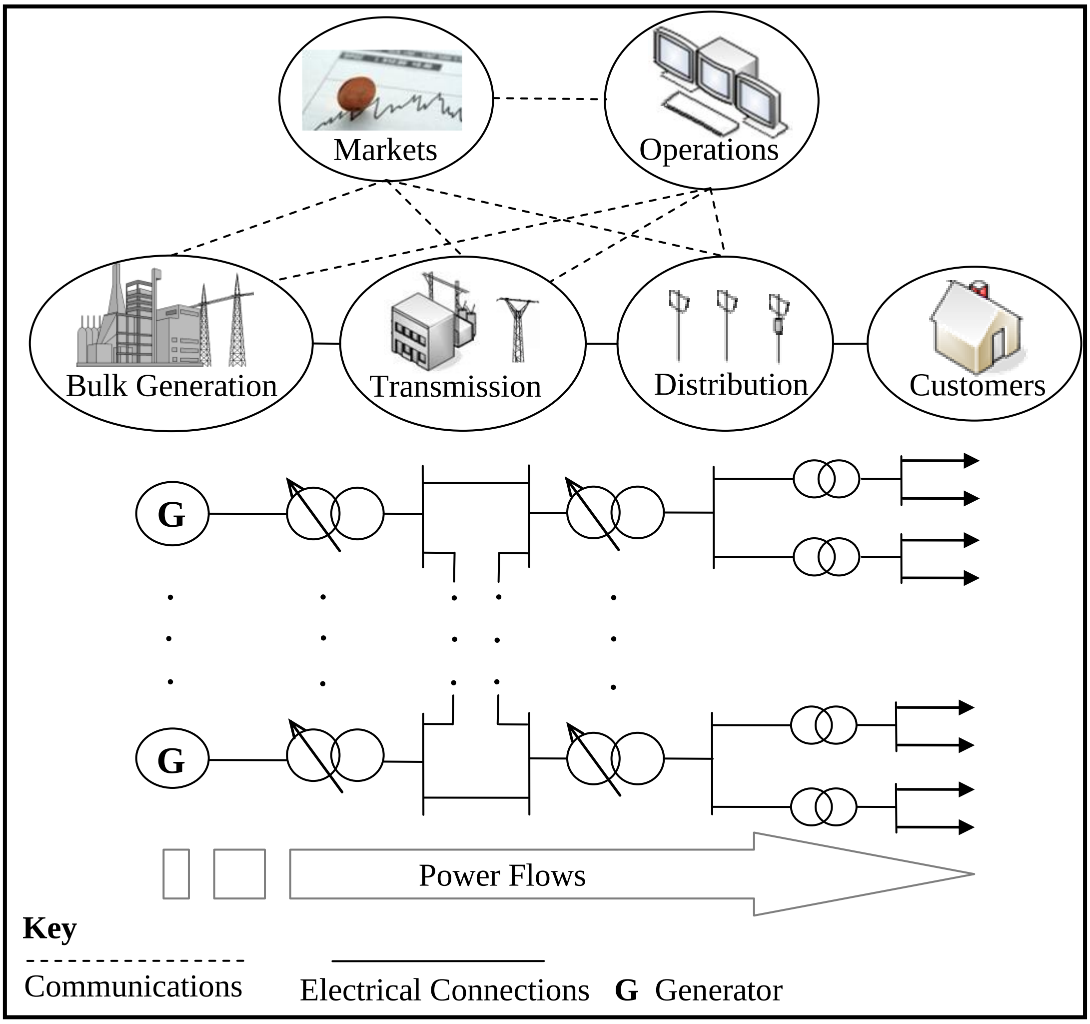


Fig.1.1 Example of conventional power system structure

The electricity distribution stage is the main stage of electricity consumption and hence of great importance for customers, in terms of meeting quality and reliability principles at a minimum possible cost and environmental impact [28]. These principles are referred to in [29] as DNOs' obligations and comprise of:

- Protection against network faults to ensure that customers are not affected by disturbances.
- Maintenance of voltages within limits.
- Assurance of equipment integrity and operation within fault ratings.
- Assistance to the Transmission System Operator (TSO) with frequency response.

DNOs typically use Supervisory Control and Data Acquisition (SCADA) systems to acquire information about the status of the distribution system through Remote Telemetry Units, or Remote Terminal Units (RTUs). RTUs are typically located from

132kV down to 6.6kV substations and they are triggered frequently to transmit data through various communication media, for the status of the equipment they monitor or control [29].

Currently, centralised SCADA systems are employed to obtain the transmitted data from RTUs to the Distribution Control Centre (DCC). There, the information is used by the Distribution Management System (DMS) to evaluate the state of the network using a number of applications that perform network monitoring, generation scheduling, generation control, network analysis and security control applications [30]. Thereafter, control signals are transmitted from the SCADA server to terminal servers sitting at substations that host Substation Control Systems (SCS) [29]. The control signals are transferred from there to downstream RTUs, other Intelligent Electronic Devices (IEDs) or generators [31]. A simplified arrangement of a SCADA/DMS system is shown in Fig. 1.2.

1.2 Future Energy Systems

Concerns over climate change and fuel security, are driving a change of the power generation mix. The UK Renewables Obligation [32] and the CO_2 emission reduction targets (80% CO_2 reduction by 2050 compared to 1990 levels [33]) are anticipated to encourage the increase of renewable and nuclear generation.

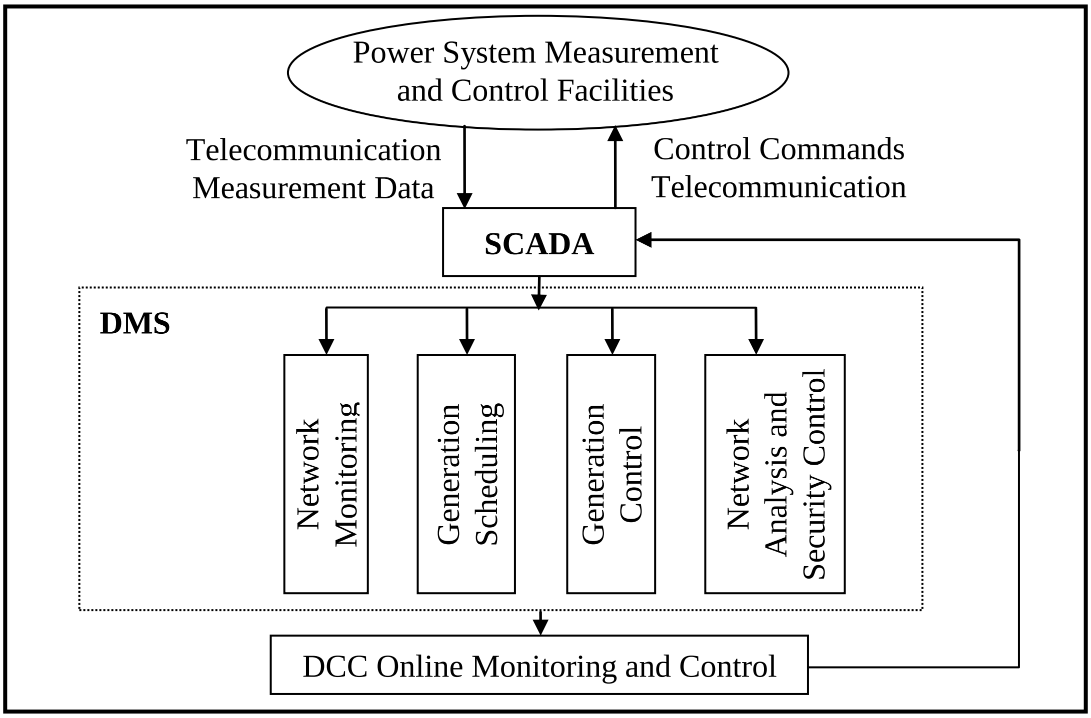


Fig. 1.2 Example function structures of centralised SCADA/DMS (Adapted from [30]-[31])

Governmental incentives, such as the feed-in tariffs for generators of a power output up to 5MW [34], are expected to increase the presence of generation that is embedded in distribution networks. This type of generation, usually termed Distributed Generation (DG), is normally smaller than 100MW [25] and can be embedded in various voltage levels of the distribution system, changing the conventional unidirectional power flows. DG plants are usually operated close to their maximum power outputs reducing the generation's mix flexibility to follow the time varying load demand.

Various technical solutions are currently employed or proposed in the literature for the integration of distributed generators into distribution networks and increase the benefits from their wide deployment. These solutions include network reinforcement, alteration of settings of network equipment such as transformer taps, and use of Active Network Management (ANM) techniques and technologies [35]. The term active network entails continuous real time monitoring, decision making and control techniques that proactively manage network and generator constraints to meet DNOs' obligations [29]. ANM is reported in [36] to include management and control of other Distributed Energy Resources (DERs) apart from generators. According to [37], Distributed Energy Resources include energy storage systems.

In the UK, DNOs have been encouraged by the Office for Gas and Electricity Markets (OFGEM) to explore ANM techniques and technologies [38]. ANM technologies include techniques and devices, with regards to: voltage control; power flow control; fault level management; ancillary services capability; energy storage; Demand Side Management (DSM); Distribution Management Systems; Energy Management Systems (EMS) and RTUs; islanding capability; power electronics; communications and smart metering [35], [39], [40].

The operation of future power networks will make Distribution Network Operators evolve to Distribution System Operators (DSOs) [41]. According to the European Union directive 2003/54/EC [42], "*Distribution System Operator means a natural or legal person responsible for operating, ensuring the maintenance of and, if necessary, developing the distribution system in a given area and, where applicable, its interconnections with other systems and for ensuring the long term ability of the system to meet reasonable demands for the distribution of electricity*". The term DSO will be used throughout this thesis instead of DNO.

The evolution of energy networks is anticipated to be encouraged by the recent regulatory framework model proposed by OFGEM [43]. According to the RIIO (Revenue set to deliver strong Incentives, Innovation and Outputs) model, increase in local generation, uptake of EVs and Energy Service Companies (ESCOs) (Fig.1.3) is required to decarbonise the energy sector and enhance security of supply. The EV uptake is particularly supported by the UK government through incentives for EV acquisition and use such as reduction in upfront costs and favourable tax regimes [44]. In addition, funds for eight pilot projects with regards to EV charging infrastructure installation and trials are reported in the Plug-in Vehicle Infrastructure Strategy [45].

The proliferation of new power system technologies and companies that provide services will increase the interdependences between power system components and enhance the complexity of power system monitoring, operation and control [29], [31]. Recently, a change is being faced from a centralised approach to monitoring and control of power systems, to a more distributed approach with distributed information processing [31].

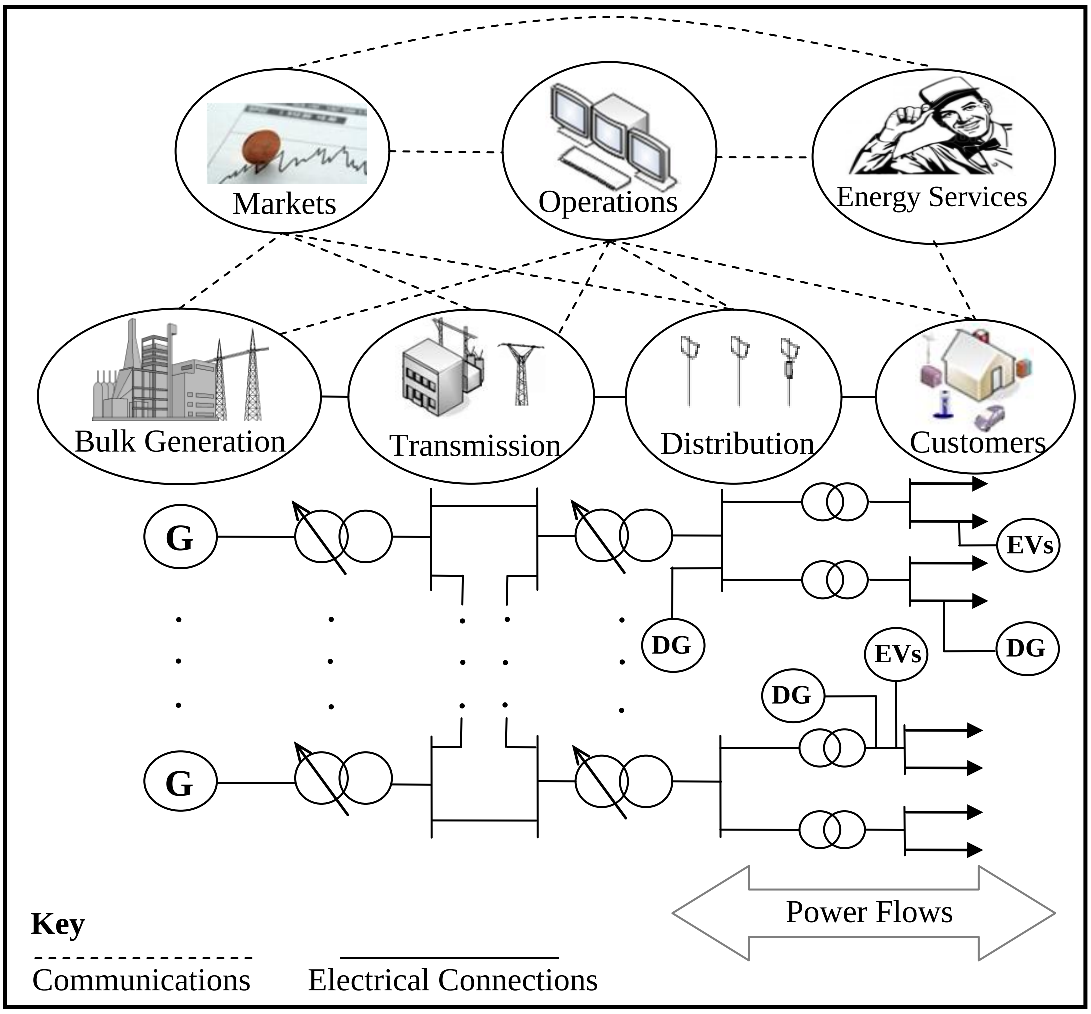


Fig 1.3 Example of power system with EVs, DGs and ESCOs (Adapted from [46])

The drivers for the change from a centralised to a more distributed approach include:

- The complexity of relationships between various power system components which are dispersed in large geographical areas.
- The need for improvements in speed, accuracy and reliability of monitoring, data acquisition and information processing.
- The difficulty in a single centralised processing entity to monitor, evaluate and control the various components in real time.
- The increased vulnerability of the power system to faults that can spread from a single component to the whole system due to increased interconnections between power system components and increased loading.

A number of technologies are being developed to provide DCCs with flexibility, and openness to continuous changes and enhancements. These include: distributed systems; object and component technology; middleware; Common Object Request Broker Architecture (CORBA) and agent technology, distributed and Service Oriented Architectures (SOA) [47]. In such architectures, EMS/DMS functions of control centres appear as modular applications and may be offered as services that can be accessed by different users, control centres and enterprises [47]-[54]. An example of control centre application services is shown in Fig. 1.4.

Battery charging of electric vehicles will generally increase electricity demand. If the process of EV battery charging is left uncontrolled, it is likely that the time that EV owners will plug their EVs in sockets or dedicated charging points to charge them will coincide with peak demands [4].

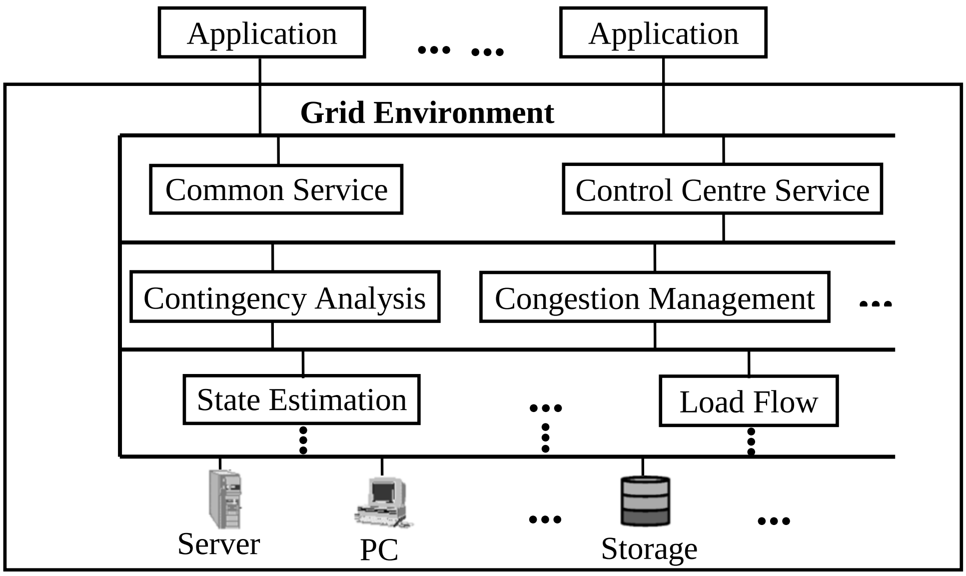


Fig. 1.4 Control centre application services [47]

There are two ways to cope with the demand increase that EV battery charging will add:

(i) To apply a passive and costly approach upgrading power system infrastructure.

(ii) To use active approaches trying to manage EV battery charging and minimise costly infrastructural updates.

A promising method for the integration of DERs in power systems that may embody the distributed processing paradigm is aggregation and control through the use of agents or Multi-Agent Systems (MAS) technology. DER aggregation aims to accumulate DER owners' preferences and DER operational characteristics, in order to form a flexible portfolio of resources. MAS technology may be utilised to make this portfolio more controllable by enabling real-time active control of these resources.

1.3 DER AGGREGATION

DER aggregation techniques and methods have been studied within major European projects including [55]-[60]. Pilot installations and laboratories have been developed [61] to demonstrate DER aggregation and control concepts [62]. It is reported in [63], [64] that with DER aggregation:

- Technical benefits can be provided to electrical power network operators, through the provision of ancillary services and deferral of infrastructure upgrades.
- Financial benefits can be provided to commercial aggregators and DER owners by enabling their participation in electricity markets.

Active customer participation or Demand Side Management is considered as a key sector of future energy networks. According to OFGEM, Demand Side Management is defined as "*any mechanism that allows a customer's demand to be intelligently controlled in response to events on the power system. Such events would include lack of network capacity or insufficient generation*" [65].

At present, in England and Wales, services from the demand side are procured by the TSO, National Grid Company [66]. These services may be provided to the TSO by single units individually, or representatives that aggregate multiple DER units to provide single points of contact [66]. These representatives are referred to as Aggregators and may be Electricity Suppliers, DSOs or ESCOs, according to [67].

In document [67] that was published for the National Grid Company, the potential of electric vehicles to provide ancillary services at the transmission level through coordination of their battery charging, was identified. In reference [68] it is reported that the use of services from the demand side could contribute to voltage support, line and distribution substation congestion relief, and power losses compensation. This thesis investigates how the load demand from electric vehicle battery charging, may be managed at the distribution level.

1.4 THESIS OBJECTIVES

The key questions that this thesis aims to address are to what is extent electric vehicle battery charging going to affect the grid demand at the national level and the steady state operational parameters of distribution networks. The following objectives were set:

1. Evaluate how different EV charging regimes and uptake levels will impact:
    - The grid demand peaks of Great Britain and Spain: Two EV uptake levels were drawn from the literature and four EV charging regimes were defined. A deterministic approach was used to evaluate the anticipated grid demand changes from EV battery charging in the year 2030.
    - The steady state operational parameters of UK distribution networks: The impact on distribution transformers' and cables' loadings, voltages of distribution feeders and electrical line losses were evaluated with a deterministic and a probabilistic approach. A case study was built for the year 2030 using three EV uptake levels and a UK LV generic distribution network model.
2. Design and develop an agent-based control system for the coordination of EV battery charging: The technology of agents was used as a coordination mechanism due to the multiple benefits it offers such as (i) proven reliability and robustness in industrial applications, (ii) simplicity and computational speed, (iii) flexibility and extensibility. The technology of neural networks for short term load forecasting was used due to (i) proven reliability and robustness in industrial applications and (ii) speed and accuracy in computations.
3. Evaluate experimentally the developed control system.

The main beneficiaries of this research are power system operators. The study presented in Chapter 3 is aimed to provide grid operators with an insight of the anticipated changes in the load profile shape and peak increase or time displacement with EV utilisation. British urban residential distribution networks are currently operated close to their capacity that is limited by equipment loading. It will be shown in Chapter 4 that if EV battery charging is left uncontrolled, distribution transformers and cables will be overloaded, power losses will be increased and the voltage profile of distribution feeders will be modified. The agent-based control system presented in Chapter 5 was shown in Chapter 6 to manage the EV load and displace it to off-peak times, keeping the distribution network parameters within their operating limits. Therefore this research is also aimed to show distribution network operators that costly infrastructural updates can be deferred.

1.5 Thesis Structure

This thesis is structured in the following way:

Chapter 2: A review of the literature related to the studies presented in subsequent chapters is given. An overview is presented regarding: (i) EV grid integration standards, (ii) EV battery charging impact on power systems, (iv) EV aggregation concepts, (v) intelligent agents and (vi) neural networks.

Chapter 3: The impact of EV battery charging on grid demand at a national level is evaluated. A case study is defined that includes different EV charging regimes and EV uptake levels. A comparison between the national systems of Great Britain and Spain for the year 2030 is presented.

Chapter 4: The impact of EV battery charging on distribution networks is addressed. Two approaches are used: (i) a deterministic approach and (ii) a probabilistic approach. A case study is defined for the year 2030 and the effect of EV battery charging on a UK generic distribution network’s steady-state operating parameters is evaluated.

Chapter 5: A hierarchical Multi-Agent System (MAS) concept for the coordination of EV battery charging is defined. The design of the MAS is analysed and the functionalities of each agent are described.

Chapter 6: The multi-agent system built in Chapter 5 was tested experimentally. The experiments were conducted in Tecnalia’s laboratory facilities in Bilbao, Spain. The hardware equipment and communication software used are described. A case study for the year 2030 was built and is defined. The experimental procedure and results are presented. The operation of the control system is evaluated.

Chapter 7: The main conclusions of this thesis are summarised. Limitations and suggestions for further work on the subject of this thesis are given.

CHAPTER 2

LITERATURE REVIEW TO ELECTRIC VEHICLE GRID INTEGRATION

2.1 ELECTRIC VEHICLE GRID INTEGRATION STANDARDS

The widespread use of Electric Vehicles will require the development of standards to ensure harmonisation and interoperability between different manufacturers, technologies and country regulations, and provide simplicity to EV owners.

European standards organisation bodies are working towards a common European standard, according to [69]. The standardisation bodies involved are: (i) Comité Européen de Normalisation (CEN), (ii) Comité Européen de Normalisation Électrotechnique (CENELEC), and (iii) the European Telecommunications Standards Institute (ETSI). The common European standard is anticipated to deal with issues regarding safety, interoperability and smart charging requirements [69].

The International Electrotechnical Commission (IEC) has announced workings on the standard IEC 62196, according to [70]. IEC 62196 is anticipated to specify types of electrical connectors between EVs and electricity networks.

The Institute of Electrical and Electronic Engineers (IEEE) has formed a Working Group (IEEE WG P2030.1) to produce a document that will serve as a guideline for utilities [71]. This guideline is being developed in cooperation with the Standards Association of Automotive Engineers (SAE) of the United States (US). Cardiff

University has been part of Task Force 2 that is concerned with the impact of EVs in power systems.

In the UK, the Energy Networks Association (ENA) has formed a task force to "*ensure that network and future smart grid requirements are fully considered in decisions affecting specification and implementation of electric vehicles and plug-in hybrid electric vehicles including those used in commercial and passenger transport*" [72]. It is reported in [72] that ENA's task force aims "*to identify work required to develop UK standards for:*

- "*connection hardware, including vehicle and charging point connectors and cables,*
- *charging points, including vehicle charge rates and types of charging station, together with recommended network requirements,*
- *wireless charging, including electrical standards and Electro-Magnetic Fields (EMF) considerations,*
- *energy metering, including data exchange and industry processes,*
- *communications and smart grid integration telling networks where vehicles are charging and telling vehicle users what can they use*" [72].

2.2 Technical Impact of Electric Vehicle Battery Charging in Power System

The charging of electric vehicle batteries will increase electricity demand. The magnitude and variance of this increase will depend on the EV uptake levels, the power rating of the EV chargers, and the connection time and duration of these vehicles to the electricity network.

2.2.1 Technical Impact of EV Grid Utilisation on Grid Demand

A number of studies that addressed the impact of EV battery charging on grid demand have been completed. In the United States, four studies have been published for the Department of Energy.

A. US Studies of EV Battery Charging Impact on Grid Demand

Electrical load demand data of six US regions were used by Denholm and Short in [73] to address filling the valley[1] in electricity demand to charge EV batteries. It was assumed that 40% of the average distance travelled in each region would be by electric vehicles and that the energy consumption of EVs would be 0.21kWh/km. The findings showed that EV charging would imply an increase in minimum load, of between 18% and 40% depending on the region under investigation.

In document [74], Kintner Meyer et al. compared the number of EVs that could be charged using a valley filling control, to the number of EVs that could be charged only during the period 18:00 and 06:00. The US national system load data from 2002 was considered and the EV fleet was divided equally into four EV technology categories, characterised by different battery capacities and energy consumption. The results showed that 84% of the vehicle fleet could be charged under the valley filling control, compared to 43% that could be charged during the period 18:00 to 06:00, according to the generation capacity of the studied year.

Hadley and Tsvetkova studied the effect of EV battery charging on the generation system of 2020 and 2030 for 13 US regions in [75]. Evening and night charging regimes were used. In the evening regime, half of the EV fleet would start the charging process at 17:00 and the rest at 18:00 p.m. In the night charging regime, half of the EV fleet would start charging at 22:00 and the rest at 23:00. Three power rating levels for EV chargers were considered for each regime: 1.4kW, 2kW and 6kW. The authors concluded that additional generation would only be necessary to cover the needs for EV battery charging, for the case of evening charging and 6kW charger use.

Parks et al. [76] considered the application of multiple charging regimes in order to study the effects of EV utilisation on grid demand for the area of Colorado in US. The charging of 500,000 EVs with 0.21 kWh/km energy consumption and 7.2 kWh battery capacities was simulated. Four charging regimes were used:

(i) Uncontrolled regime: charging of EVs starts as soon as they return home.

(ii) Delayed regime: charging of EVs starts at 22:00.

(iii) Off- peak regime: charging of EVs starts at 23:00 and stops at 07:00.

(iv) Continuous regime: EVs are charged throughout the whole day.

[1] Load demand valley filling typically means the flattening of a load profile

It was assumed in [76] that the charger rating for each regime was 1.4kW except for the off-peak regime, in which 3.2kW chargers were considered. The uncontrolled regime case resulted in an increase of 2.5% in peak demand. The continuous regime would increase the peak demand by 4.6%.

B. EU Studies of EV Battery Charging Impact on Grid Demand

In document [4] that was published for the British government, the annual energy demand required to cover the EV battery charging needs for different EV uptake levels in the UK, was calculated. It is reported that the EV battery charging demand would be between 4.2TWh-31TWh (1.1%-7.9%) assuming a total electricity demand of 390TWh for the year 2030. The EV uptake levels used in [4] are shown in Table 2.1 and the annual calculated EV energy demand for each level is shown in Table 2.2.

The authors of document [4] concluded that UK's generation will be sufficient to cover the calculated EV battery charging demand, assuming that this demand will be managed with ways that will aim to avoid EV battery charging occurrence during peak load hours. However, this issue was not further studied.

Table 2.1 Projected number of BEVs and PHEVs in the UK according to [4]

Year	**2020**		**2030**	
Scenario/*EV Type*	*BEV (units)*	*PHEV (units)*	*BEV (units)*	*PHEV (units)*
Business as Usual	70,000	200,000	500,000	2,500,000
Mid-Range	600,000	200,000	1,600,000	2,500,000
High-Range	1,200,000	350,000	3,300,000	7,900,000
Extreme Range	2,600,000	500,000	5,800,000	14,800,000

Table 2.2 Annual EV electricity demand in the UK according to [4]

Year	**2020**	**2030**
Generating capacity	100GW	120GW
Projected annual UK demand	360TWh	390TWh
EV demand	**GWh**	**GWh**
Business as Usual	400	4,200
Mid-Range	1,800	6,700
High-Range	3,500	17,000
Extreme Range	7,400	31,000

Researchers from the Caledonian University of Glasgow [77] studied the effect of EV battery charging on the grid demand of GB. A 10% EV uptake based on 2008 car fleet figures (that translates to 2.84 million cars) and grid demand data for the year 2009 were used. The charging characteristics of three types of batteries were used with a maximum power rating of 7kW. Three charging regimes were considered:

(i) Uncontrolled regime: charging of EV batteries occurs at the last daily trip home arrival time, which is between 17:00-18:00 for company vehicles and 17:30-18:30 for private vehicles.

(ii) Off-peak charging regime: charging of all EV batteries starts between 21:00-22:00 and stops at 06:00.

(iii) Smart charging regime: charging of all EV batteries occurs during the cheapest hours of the day in terms of electricity prices. The starting time for charging was assumed between 23:00-24:00 and the ending time at 07:00.

The results from study [77] showed that:

1. If EV batteries would be charged every day:
    - The uncontrolled regime would increase the winter peak demand by approximately 10%.
    - The off-peak regime would increase the winter peak demand by 6.1%.
    - The smart charging regime would not increase the winter peak demand.
2. If EV batteries would be charged every two days:
    - The uncontrolled regime would increase the winter peak by 5.84%.
    - The off-peak regime would not increase the winter peak demand.
    - The smart charging regime would not increase the winter peak demand.

The European project Mobile Energy Resources in Grids of Electricity (MERGE) examined the effect of residential EV battery charging on electricity demand of six European countries, including GB and Spain [78]. Two EV charging regimes were used:

(i) Dumb charging: EV owners would plug-in their EVs as soon as they return home from the last daily trip.

(ii) Smart charging: a valley filling approach is adopted.

Study [78] used the following assumptions:

- The average energy requirement of each EV per day is 6.4 kWh.
- The efficiency of EV chargers is 90% and the rated power is 3kW.
- The EV uptake is 10% of each country's car fleet in 2009.
- The grid demand excluding the EV demand comes from typical summer and winter days of 2009.

The results reported in [78] show that a dumb charging regime would increase the peak demand of the six countries examined between 6% and 12%.The peak demand of GB would increase by 8% and the peak demand of Spain by 7%. The valley filling control showed that the specific EV uptake examined, would not increase the daily peak demand of any country under investigation.

C. <u>Contribution of this Thesis on EV Battery Charging Impact on Grid Demand</u>

In Chapter 3 of this thesis, the effect of residential EV battery charging on the electricity demand peaks of the national systems of GB and Spain is examined. The study is an outcome of collaboration with the research institute Tecnalia in Spain and was submitted for publication before studies [77]-[79] became publicly available. However, it will be shown in Section 3.7 that the results from the three studies are in good agreement.

The present study differs from study [77] in the following points:

- The present study investigated the effect of uncontrolled, dual tariff, variable price and mixed charging regimes for residential battery charging of EVs. The definition of these regimes is provided in Section 3.4 of Chapter 3. Study [77] did not investigate a mixed charging regime.
- The present study used scenarios for the EV uptake and grid demand for the year 2030. Study [77] used EV uptake data for the year 2008 and grid demand data for 2009.
- The present study investigated the effect of residential EV battery charging on grid demand peaks for the Spanish system as well.

The present study differs from study [78] in the following points:

- Study [78] investigated only uncontrolled and valley filling charging regimes.
- Study [78] investigated the effect of a 10% EV uptake of the vehicle fleet of 2009 on the grid demand of the year 2009.

2.2.2 Technical Impact of EV Grid Utilisation on Distribution Networks

Several studies that address the impact of EV battery charging on power distribution networks have been completed. While there are some similarities across these studies, each of them considers a different approach in terms of the electric system, analysis method/software, electric vehicle uptake and charging scenarios analysed. A summary of the reviewed studies is provided in Table 2.3.

Table 2.3 Summary of documents that addressed EV impact on distribution networks

Electricity network	EV related assumptions	Method/ software	Study aims	Source
Distribution network in US with 1232 customers.	10 PHEV uptake levels from 0 to 100%. EV charger of 1kW. The charging period is 17:00 -23:00.	Load flow studies with PHEV Distribution Circuit Impact Model (PDCIM).	Impact on underground cables and transformers.	[79]
Distribution transformer feeding three residences.	Two EV chargers of 120 V, 15 A used in charging period of 21:00-08:00. One EV charger of 240V, 30 A used in a charging period of 00:00-03:00.	Use of first order electro-thermal model for a distribution transformer.	Impact on loss of life of the transformer.	[80]
Energy hub network including electric, heat loads and PHEVs.	PHEVs are introduced as software agents into energy hub networks.	Integration scheme for PHEVs into power networks, modelled within energy hubs.	Assessment of energy hub network with Multi-Agent Transport Simulation (MATSIM).	[81]
MV network, supplied by a HV/MV transformer and five DG units.	EV uptake levels of 25% and 50%.	A mobility model and stochastic system loading is used for load flow studies.	Distribution of node voltages and cable overloads with/without EVs and smart charging.	[82]
Portuguese semi-urban 15kV	1.5 vehicles per household on average. Three EV types;	Load flow studies with PSS®E and stochastic inputs.	Impact on transformer and line	[83]

network.	Hybrid EV: 1.5 kW (6 kWh), Medium EV: 3kW (12 kWh), Large EV: 6 kW(24kWh).	Algorithm to maximize the EV charging.	loadings, node voltages and network losses.	
Detailed distribution network from MV substation to service entrance.	EV uptake levels of 2%, 5% and 10%. Two EV chargers of 12A (120V) and 30A (240V) were used for peak and off-peak load conditions.	Deterministic and stochastic analysis using Distribution Systems Simulation Model (DSSM) software.	Impact on thermal loadings, unbalance, harmonic distortion and power losses.	[84], [85]
IEEE 34-node test feeder was scaled to 230V to represent a residential network.	PHEV uptake levels of 10, 20, and 30%. EV type: 4kW (11kWh). Three charging periods: 09:00-18:00, 18:00-21:00, 10:00-16:00.	Stochastic inputs for EV charging duration and SoC were used as inputs to a load flow algorithm.	Optimisation aiming to minimise network losses.	[86]
3-node network with co-generation and a PHEV aggregator.	PHEV uptake levels of 10% and 30%. Three charging periods: 10:00-17.59, 09:00-20.59 and continuous.	Time Coordinated Optimal Power Flow (TCOPF) with gPROMS™ software.	Optimisation aiming to minimise network losses.	[87]
Two distribution networks from the US.	PHEV uptake levels of 10%, 25%, 50% and 100%. Two EV charger types: 15A (120V) and 40A (240V).	SynerGEE® load flow analysis tool.	Impact on distribution substation equipment loading.	[88]
UK LV generic distribution network.	EV uptake levels of 10% , 20%, 30%. Three charging scenarios: uncontrolled, off-peak and smart charging.	Deterministic load flow and statistical analysis.	Impact on distribution transformer, node voltages, power quality, and imbalance.	[89]
Two distribution networks of 6,121 and 61,304 supply points.	EV uptake levels of 35%, 51% and 62%. Peak and valley charging were tested. Four EV types with four charging rates each.	Steady-state load flow studies.	Calculation of the reinforcement required to accommodate the EVs.	[90]
Danish distribution network with wind generation.	EV uptake levels of 10% and 20%. A peak load system scenario was studied. EV type: 16A, 230V (16kWh).	Deterministic and probabilistic analysis is used for load flow studies.	Impact on voltage profile of distribution feeders.	[91]

German suburban distribution network.	EV uptake levels of 2.5, 10 and 25% Four types of EV chargers: 2.7, 4.6, 14 and 60kW.	Deterministic load flow studies.	Impact on distribution transformer loading.	[92]
Dutch LV distribution network.	EV uptake level of 75% was used. Two types of EV chargers: 3 and 10kW.	Deterministic load flow studies.	Impact on transformer and cable loadings and node voltages.	[93]
UK distribution system.	EV uptake levels of 10% and 20% were used.	Stochastic analysis and deterministic load flow study.	Impact on load profile and line congestion levels.	[94]

The majority of the studies presented in Table 2.3 used load flow based simulations to address the impact of EV battery charging on:

- Thermal loadings (congestion levels) of distribution transformers and cables.
- Voltage of distribution network nodes and feeders.
- Power line losses.

A. <u>Deterministic Studies</u>

Deterministic studies are categorised into single-snapshot and multi-period studies.

In single-snapshot studies, fixed locations and power ratings for EV chargers and fixed values for the remaining distribution network loads are used. Load flow algorithms have been executed to determine the states of the equipment and operational parameters of the network for the given configuration [84], [88], [92].

In multi-period studies, daily simulations have been performed, assuming that EV charging locations and EV charging periods would be fixed. Daily load profiles have been used for the remaining system's loads [79], [80], [87], [89], [90], [91], [93].

B. <u>Probabilistic Studies</u>

Probabilistic studies used stochastic procedures to define distribution network loading conditions and acquire probability densities of the operational parameters of the studied networks.

In document [82], the plug-in time and duration for each EV were acquired by a mobility model for a full year. In reference [83], the connection of EVs was assumed to coincide with home arrival, based on Portuguese traffic patterns, and the duration of charging was assumed to be four hours. Daily sequential power flows were executed to obtain probability densities of nodal voltages, thermal loadings and losses. In document [86], three charging periods of EVs were predefined and a centralised scheduler was used to optimise the charging rates of each EV for each hour of each period, within distribution network voltage and cable limits. In reference [91], the charging patterns of the EVs were extracted from the traffic pattern of conventional vehicles and nodal load values were created to execute 50 load flows per hour for a daily simulation. The study outputs were mean hourly node voltage values.

C. Contribution of this Thesis on EV Battery Charging Impact on Distribution Networks

In Chapter 4 of this thesis, deterministic and probabilistic studies are presented using a typical British LV distribution network. Both studies evaluated the impact of EV battery charging on distribution transformers and LV cable loadings, node voltages and power line losses. It was assumed that the single-phase connections were distributed evenly across the three phases and therefore voltage unbalance studies were not conducted. EV uptake estimates for the year 2030 were used.

i) The deterministic study presented in Chapter 4 shows single steady state load flow snapshots using a UK generic LV distribution network for minimum and maximum loading conditions. The study method is similar to the studies [84], [85], [88] however, it differs in the data and electrical network used. The data used are estimates for the UK for the year 2030 and the LV distribution network model used comprises a representative configuration for British distribution networks. The same network was used in [89], with data for the year 2003, but the impacts on electrical line losses and distribution transformer and cable loading were not investigated. The present study showed that EV battery charging will overload the cables and transformers, and modify the voltage profile of distribution feeders of the network under investigation. A network reinforcement approach is evaluated. Different EV uptake levels are used for the evaluation of the studied impacts using various reinforcement combinations of underground cables and distribution transformer. A case where micro-generators are installed is also evaluated.

ii) The probabilistic study presented in Chapter 4 shows probability densities of the studied impacts using seasonal daily load profiles and sequential power flows.

A number of impact factors were modelled as uncertain variables: (i) residential load profiles, (ii) EV types, (iii) EV charging equipment power rating and locations, (iv) EV charging connection time and duration, (v) micro-Generation (mGen) types, generation profiles and locations of installations. The first three factors have been considered in [82], [83], [86], [91] but the remaining factors are introduced in the present research. A smart charging function is evaluated.

2.3 EV AGGREGATION AND CONTROL CONCEPTS

The aggregation of EV resources to provide services to electricity system operators and enable EV participation in electricity markets is a recent concept. A number of studies that address the use of EV batteries to provide power system frequency related services to TSOs, have been completed [83], [95]-[102]. This section reviews the literature with regards to aggregation of EV resources, focusing in particular on concepts that study the coordination of EV battery charging based on EV owner preferences and distribution network constraints.

2.3.1 Definition of Aggregator Types

The company types identified in the literature to aggregate DERs, are ESCOs, Energy Service Provider Companies (ESPCs) and simply Aggregators.

An ESCO, according to a report prepared for the European Commission [103], is "*a natural or legal person that delivers energy services and/or other energy efficiency improvement measures in a user's facility or premises, and accepts some degree of financial risk in so doing. The payment for the services delivered is based (either wholly or in part) on the achievement of energy efficiency improvements and on the meeting of the other agreed performance criteria*".

In contrast to ESCOs, ESPCs are "*natural or legal persons that provide a service for a fixed fee or as added value to the supply of equipment or energy. Often the full cost of energy services is recovered in the fee, and the ESPC does not assume any (technical or financial) risk in case of underperformance*" [103].

An aggregator, according to the European project birth of a European Distributed Energy Partnership (EU-DEEP) [104], is a "*legal organisation that consolidates or aggregates a number of individual customers and/or small generators into a coherent group of business players". "An aggregator is therefore a facility manager able to design and offer energy services downstream to energy customers (at the micro level:*

a large number of contracts) and upstream to several key players (at the macro level: system operators, electricity traders, etc.)". "*Aggregators can also be viewed as entities that bring a group of consumers together to buy electricity*" [104].

At present, in the UK, only companies that hold a supplier's license are allowed to supply electricity. These companies cannot hold a license of a DSO, according to the UK Electricity Act [105]. Supplier companies have been developing special electricity tariffs for EV charging [106] and cooperating with EV charging point and EV manufacturers [107].

In document [108] of the European project MERGE, it is reported that with the current regulation it is more justifiable to consider EV aggregators as parts of energy supplier companies or the supplier companies themselves. A control and management framework for EV aggregation was developed within MERGE [109]. According to that framework [109], the company that aggregates EV demand and coordinates EV battery charging, was named Electric Vehicle Supplier/Aggregator (EVS/A). A number of agents that have been developed to coordinate EV battery charging and presented in Chapter 5 of this thesis are assumed to belong to such a company. The locations of the agents in a power distribution system are provided in Section 5.2.

2.3.2 Aggregation and Control Concepts of Electric Vehicles in Distribution Networks

Two approaches are currently found in the literature with regards to coordinated control of EV battery charging considering distribution network technical constraints: (i) centralised control and (ii) distributed control.

A. Centralised Control of EV Battery Charging

In centralised control approaches, optimisation algorithms have been used to obtain optimal schedules for charging EV batteries within distribution network limits and:

- Minimise power losses [86], [110], [111].
- Minimise voltage deviations on distribution feeders [112].
- Maximise the amount of energy delivered for EV battery charging [113].
- Minimise the cost of charging for the EV owners [114]-[118].
- Fill the valley of the load curve at the primary and secondary distribution transformers, by minimising the load demand variance [119].

The studies [86], [110]-[119], assumed that the relevant data for each EV and measurements for each node of the electrical network would be transferred to a centralised controller. Thereafter, optimal power flows or other similar algorithms would be executed for finite horizons (i.e. a day) and individual EV schedules would be obtained. The EV schedules would be transmitted to EV controllers and the set-points at each time instant would be applied.

In document [120] that was published from International Business Machines (IBM), it is argued that the responsible company for managing EV battery charging (termed in [120] EV fleet operator) should be separated from the DSO, and thus not have access to the topology of the distribution network. However, it is assumed that the loading limits of the network would be made available to this fleet operator before the decision making procedure.

The assumptions made in documents [86], [110]-[120] to obtain EV charging schedules within distribution network constraints are summarised:

1. Predictions for distribution network loading conditions would be in place prior to the optimisations.
2. The characteristics of all EVs (i.e. battery charging efficiency and technology) are identical to reduce the variables of the optimisations.
3. The EV owners' preferences (i.e. EV connection and disconnection times, and energy requirements) would be known or predicted before the optimisations.

The centralised approaches of the reviewed studies [86], [110]-[120] do not report addressing control in real-time. Moreover, the calculation process is reported to be time consuming and resource-expensive [119].

B. Distributed Control of EV Battery Charging

In distributed control approaches, the problem of finding individual EV profiles that satisfy a set of requirements is broken into smaller sub-problems and the computations for each sub-problem are executed separately. The EV owners and EV aggregators are represented by software agents. An agent is a piece of software that is able to perceive its environment through sensors and act to that environment through actuators [121]. For example, an EV agent represents the EV owner and communicates with other agents to decide its charging schedule and satisfy the Aggregator's policy. More details on agents are provided in Section 2.4.

Researchers from the University of Michigan, California Institute of Technology and Carnegie Mellon University of the US [122]-[124], addressed filling the valley of the load curve using finite-horizon non-cooperative dynamic game theory approaches. The proposed algorithms aim to obtain individual schedules for EVs satisfying energy capacity limits. A planning period between EV agents and a coordinator agent that represents the aggregator takes place prior to the energy delivery. The main process is summarised:

1. The EV agents provide the coordinator agent with their decision (charge or idle) for each interval of their connection period.
2. The coordinator agent updates an energy cost value based on the total load demand (which is EV charging demand plus the remaining system loads) and distributes this value to the EV agents.
3. The EV agents re-evaluate their decision based on the received cost value and the EV owner preferences.

The above process is repeated until all EV agents remain on their decision. The coordinator agent is assumed to know the available energy for trading. The link with the electrical network is not mentioned in [122]-[124].

Researchers from Leuven University of Belgium [119] proposed an MAS where one coordinator agent is located at the MV substation and one coordinator agent at the LV substation. The aim of the MAS is to flatten the load profile at both MV and LV transformers. Two operating alternatives are proposed:

i) Each EV agent sends the power rating and energy requirements to the LV substation agent. The LV substation agent schedules the charging of the EV for the whole duration of the EV connection, in communication with the MV substation agent. Load forecasts for the remaining loads of the distribution network are assumed to be in place for the whole period.

ii) Each EV agent sends only the power rating of the charging point to the LV substation agent that decides in communication with the MV substation agent whether each EV will charge at the next time interval.

The first alternative showed that the variance of the load profile was lower than in the second alternative.

Researchers from Southampton University of England [125]-[126], proposed an MAS where a coordinator agent is assumed to know the amount of energy that can be allocated to the EVs during a given period and proposed an algorithm that intends to incentivise EV owners to report truthfully the duration of the EV connection in order to avoid discrimination. It is reported in [125], that the algorithm accomplishes that, by leaving electricity units unallocated. The algorithm does not take into account arrivals of EVs during the given scheduling period.

C. Contribution of this Thesis on Control of EV Battery Charging

Distributed management and control of EV battery charging concepts [122]-[126] do not report interactions between aggregator companies and the DSO. Furthermore, unforeseen circumstances such as emergency events are not addressed.

The technology of Multi-Agent Systems is used in Chapter 5 of this thesis for the development of a control system that considers:

- Real-time uncertainties.
- Interactions between the aggregator and the DSO.
- Emergency events.

2.4 Distributed Control Systems, Agents and Multi-Agent Systems

Distributed control technologies have been used by numerous researchers in recent years in power engineering applications. Two distinct technologies of distributed computing have been employed by utilities; SOA [54] and MAS [127].

SOA is currently used in Spectrum Power Control System developed by Siemens [54] and utilised by the Spanish electric utility Iberdrola. SOA is a computing paradigm that aims to support high performance, scalability, reliability, and availability [47]. Services are applications that run on a cluster of centralised servers and may be accessed through programmable interfaces [47]. The hardware resources required for the execution of these applications may be split among various machines to accelerate the process. This is called Grid Computing [47], [128]. In SOA, the registration and search for each service is done through a mediator (i.e. broker). When the communication between a client (i.e. service requester) and a server (i.e. service holder) is implemented via the web using particular types of machine readable protocols (such as eXtensible Markup Language or XML), then this type of SOA is called Web-Services architecture according to [47], [128]-[129].

A web-service can be seen as an application provided by an agent [47], [130], or conversely, an agent may use a web-service [131]. There are some distinct features of agents that differentiate them from services. According to Jennings and Wooldridge [132], agents and MAS adopt the object-oriented paradigm by keeping the information needed to solve each sub-problem private. Moreover, they enhance this paradigm by incorporating control over their actions [132].

The basic properties of an agent, according to [133], are:

- Autonomy: the ability to operate in order to meet its design objectives without constant guidance from the user.
- Responsiveness: the ability to perceive the environment and act in response.
- Social ability: the ability to interact with other agents.
- Pro-activeness: the ability to reason and initiate its own actions in order to meet its design objectives.

The above characteristics differentiate agents from objects and web-services, in the sense that an agent may have the ability to decide upon its actions, according to the resources, skills and services that it may possess and access [132]. In addition, communication and interaction between agents in MAS can be carried by a richer set of standards that may support interoperability [128]. Such standards were proposed by the Foundation of Intelligent and Physical Agents (FIPA) [134].

According to McArthur et al. [128], "*applications where the use of agents is justified are normally cases where the characteristic of autonomy offers tangible benefits*". In the MAS proposed in Chapter 5 of this thesis, the property of autonomy is employed for the operation of the MAS in normal operating conditions and in emergency operating conditions. In this thesis, normal operation refers to distribution network operation within technical limits and emergency operation refers to operation when distribution network technical limits are violated. During emergency operation, the MAS acts autonomously to restore normal operating conditions.

The technology of MAS has been used in a range of applications in power system engineering. Distinguished examples of MAS technology use in real world power engineering industrial applications include:

- The ARchitecture for Cooperative Heterogeneous ONline Systems (ARCHON^{TM}) system developed by EA Technology and the University of Southampton. The use of ARCHON^{TM} for power system diagnostics and outage management in a system operated by the Spanish electric utility company Iberdrola, is reported in [135].

- The Protection Engineering Diagnostic Agents (PEDA) system for data retrieval and analysis developed by the University of Strathclyde. The use of PEDA to support protection decision making in a transmission system operated by the British Company Scottish Power Powersystems, is reported in [136].

- The IntelliTEAMII system developed by S&C Electric Company has been used for outage management and service restoration in a Canadian power distribution system operated by ENMAX Power Corporation [137].

A number of laboratories exist that host DER and have been used for developing and testing agent-based applications for DER aggregation. Important examples are:

- The laboratory in the National Technical University of Athens (NTUA) [138].

- The laboratory in Tecnalia research institute [139].

- The laboratory in Durham University [140].

2.4.1 Foundation of Intelligent and Physical Agents (FIPA)

FIPA is a standards committee of the IEEE Computer Society. FIPA develops specifications and standards that support interoperability among agents and agent based applications [141]. A FIPA compliant Multi-Agent System MAS should follow the formation described in the Agent Management Reference Model [142] which provides "*the normative framework within which FIPA agents exist and operate. It establishes the logical reference model for the creation, registration, location, communication, migration and retirement of agents*" [142].

Each module of the reference model is a necessary component for a FIPA-compliant MAS [142]-[143]. Agents are loaded on an Agent Platform (AP) that provides the physical infrastructure on which agents are deployed. Each agent may provide a service as part of the MAS and may have access to resources and posses skills, both denoted in Fig. 2.1 as Software [142]. The service of each agent can be published in the Directory Facilitator (DF) that provides yellow pages services.

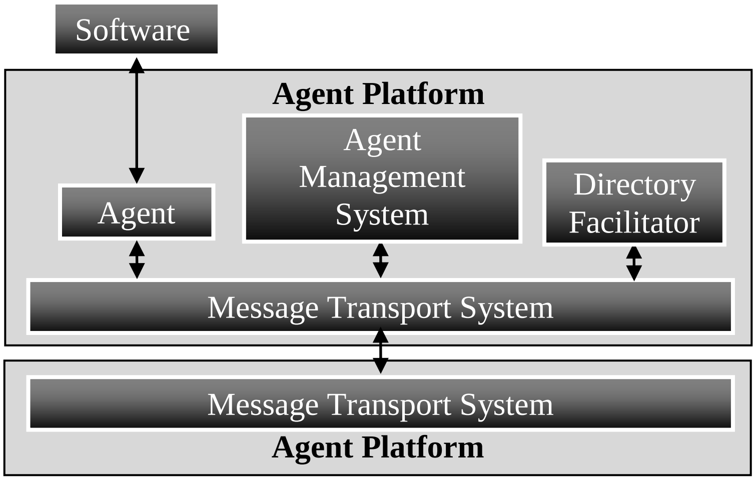


Fig. 2.1 Agent management reference model [142]

A mandatory component of an agent platform is the Agent Management System. The Agent Management System manages the operation of the agent platform providing unique identification addresses-Agent Identifiers (AIDs) to each agent hosted in the platform and maintaining the agents' status in its directory [142]. The Message Transport System (MTS) transports intra-platform and inter-platform FIPA-compliant messages between agents [142]-[143]. The language of the messages is the Agent Communication Language (ACL) [144]. The structure of an ACL message is shown in Fig. 2.2.

The ACL messages that are transported between agents may comprise of various parameters with the type of communicative act (performative) being the only mandatory parameter. The Agent Communication Channel (ACC) is provided by the AP and offers the MTS that uses the message transport information included in the message's envelope to transport the message. Interaction Protocols (IPs) are standardised communication patterns which provide a pre-defined sequence of communicative acts between agents. FIPA's IPs' specifications can be found at [145].

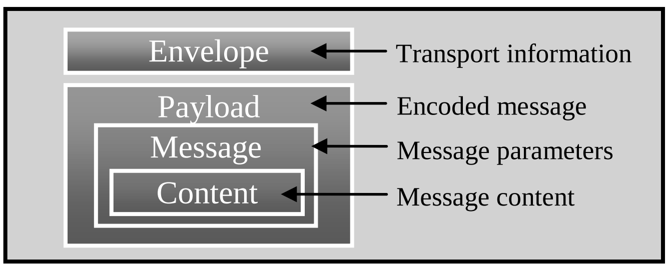


Fig. 2.2 FIPA ACL message structure [142]

2.4.2 Agent Development Software Selection

Numerous agent development software packages are available, each offering different functionalities. Discussion and evaluation of more than 50 packages can be found in references [146]-[157]. The main criteria for the choice of the package were: appropriateness for the specific application and active developer society/high activity.

Table 2.4 presents the most appropriate software packages that were considered after the literature review, due to their FIPA compliance. JACK® and JADE software packages have proved robustness and reliability in industrial applications [158], [159]. JADE was the package used in this research due to the following reasons:

(i) High activity of JADE community, with continuous updates of source code.

(ii) Proven reliability and robustness [160] in simulation studies and real world applications, including major European projects [55]-[60] and power engineering applications [138]- [139].

2.4.3 JAVA™ Agent Development Framework (JADE)

JADE provides all the facilities required to develop an agent-based application:

- Distributed runtime environment that implements the life-cycle support features required by agents.
- A library of classes that developers can use to implement their agents.
- A suite of graphical tools that facilitates the debugging, administration and monitoring of the executed agents.
- The Agent Management System and the Directory Facilitator.

Table 2.4 Comparison of agent development software

Software	FIPA-Compliance	Availability	Activity	Source
JADE	Fully	Public	High	[158]
JACK®	Not Readily	Commercial	Medium	[162]
Agent Factory	Fully	Public	Low	[163]
Zeus	Fully	Public	Low	[164]
Comtec	Fully	Public	Low	[165]
FIPA-OS	Fully	Public	Low	[166]
Tryllian	Fully	Public	Low	[167]

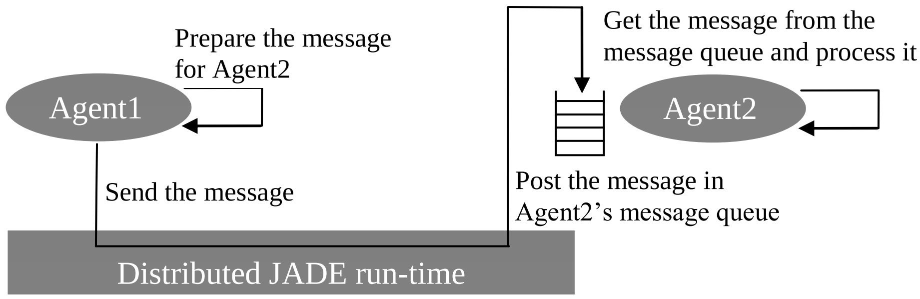


Fig. 2.3 JADE communication architecture [142]

Each JADE agent has a unique identity that includes its name and address and is contained within an AID. The agent addresses are transport addresses inherited by the platform, where each platform address corresponds to a Message Transport Protocol (MTP) end point in which FIPA-compliant messages can be sent and received.

The tasks performed by an agent are carried out within a code format which is called *behaviour*. A *behaviour* is implemented as an object of an abstract class that provides the skeleton of the task to be performed [142]. This class is provided by JADE and can be modified or enhanced according to the needs of the programmer. The communication between agents is based on asynchronous message passing [142]. When an agent sends a message to a recipient, this message is stored to the recipient's message queue through the JADE run-time [142]. The recipient is then notified. However, it is at the discretion of the developer when, or if, the agent is going to pick up the message from the message queue (Fig. 2.3).

The structure of each JADE agent consists of three layers [142] (Fig. 2.4):

1. Message handling layer enables communication with other agents.
2. Behavioural layer contains the core decision making software of the agent (i.e. agent logic).
3. Functional layer is used by the agent to apply an action to a physical entity (for example sending a set-point to a battery inverter).

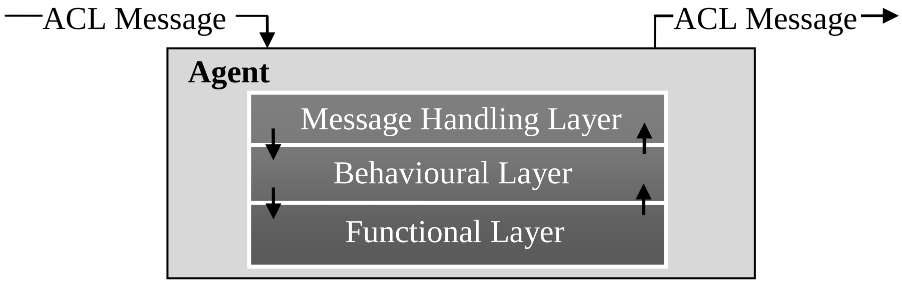


Fig. 2.4 Layered structure of a JADE agent [142]

2.4.4 Short Term Load Forecasting with Artificial Neural Network

In multi-agent systems where forecasts of electrical load in the very short term (i.e. less than an hour) were required, the methods of persistence [168] and linear regression [169] were used. Persistence means that the agent assumes that the load demand in the following time interval will be the same with the load demand in the current time interval.

In document [128], it is reported that the technology of MAS provides a framework where Artificial Intelligence (AI) techniques may be integrated. Numerous methods for short term load forecasting have been developed. According to [168], these include: similar-day approach; regression methods; time series; neural networks; expert systems and fuzzy logic. The use of Artificial Neural Networks (ANNs) for the forecasting of electrical load by the Greek utility Public Power Corporation is reported in [171]. In the proposed MAS in Chapter 5, the technology of ANNs is used. This subsection provides a brief theoretical background of ANNs.

Artificial neural networks are information-processing systems that represent biological neural networks through mathematical models [172]. A biological neuron has three main components; dendrites, soma and axon. The dendrites receive signals from other neurons. These signals are transmitted across a synaptic gap via a chemical process. This process modifies the signals which are then received in the soma of the neuron. The soma sums the incoming signals and when sufficient inputs are gathered, the soma is activated to transmit a signal via its axon to other neurons [172].

To represent a biological neuron through mathematical relationships, two assumptions are generally made [172]. The first is that the modification of each signal received via a neuron’s connection is modelled with a weighted multiplier w, called synaptic weight. The second is that each neuron applies an activation function to its net input (sum of weighted input signals) to determine its output signal.

An artificial neural network, according to [172], is described by:

- The architecture: the pattern of connections between neurons.
- The training algorithm: the method of determining the weights of its connections.
- The activation function.

Several neural network types have been developed. Many versions or variations/combinations may be found in the literature with respect to ANN types. According to [172], [173], basic neural network types include: Feed Forward Neural Networks; Self Organizing Map Neural Networks; Recurrent Networks; Radial Basis Function Network; Learning Vector Quantization. The most common type of ANN reported in the literature is the Multi-Layer Perceptron (MLP). This type of ANN is a feed-forward ANN and is used in this thesis.

The basic unit of the MLP is the perceptron. It produces its output by taking a linear combination of the input signals and transforming this through its activation function. MLP networks consist of several layers of neurons. Each neuron of a certain layer is connected to each neuron of the next layer. An MLP comprises of at least one input layer, one hidden layer and one output layer. Each layer may comprise a number of neurons.

Fig. 2.5 (a) shows a simplified representation of a biological neural network with inputs x_n from four neurons in the input layer, a processing unit of one neuron in the hidden layer, and output y_n to two neurons in the output layer. Fig. 2.5 (b) shows the representation of the artificial network in a simplified diagram.

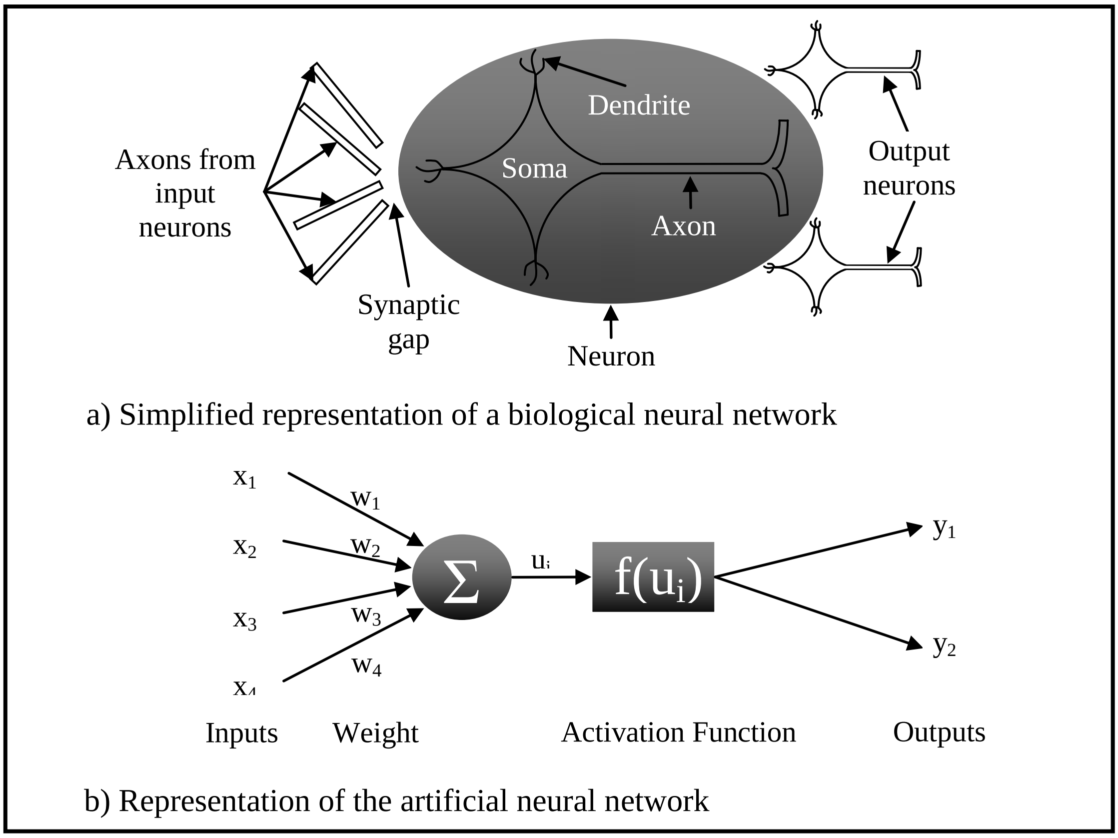


Fig. 2.5 Example of three-layer neural network

The training of ANNs is done through supervised algorithms or is left unsupervised. In MLP ANNs, supervised training is commonly used. The ANN of this thesis is trained with supervised training. Details on unsupervised training of neural networks can be found in [173]-[176]. Supervised training algorithms in ANN are used to learn the relationship between a set of network inputs and a set of desired outputs and adjust the weights of the network connections [177]. A number of supervised training algorithms for ANNs can be found in the literature. According to [177], these include; Back Propagation; Resilient Propagation; Manhattan Update Rule; Levenberg Marquadt; Scaled Conjugate Gradient; Neural Network Simulated Annealing Training; Neural Network Genetic Algorithm Training.

Propagation training algorithms are commonly used to train MLP ANNs. In general, propagation training algorithms are gradient descent methods; at the beginning of propagation training algorithms, the synaptic weights are given small random numbers and the training error between the desired and the actual outputs is calculated. The training iterations continue for the whole training dataset, until the gradient of the average error falls below a predefined threshold [172]. At every iteration the weights are updated. The minimisation of the error and the updating of the weights depend on the training algorithm used. Resilient propagation (RPROP) is reported as a very fast propagation method in terms of convergence in [178]. An improved method of the RPROP algorithm is called improved resilient propagation ($iPROP^+$) [179] and its implementation in [180] is used in the training of the developed MLP. The description of the $iPROP^+$ algorithm is provided in Appendix A.

According to [180], activation functions for ANNs include: Bipolar; Competitive; Gaussian; Linear; Logarithmic; Sigmoid; Sinusoidal; Hyperbolic Tangent. The hyperbolic tangent activation function is commonly used in ANNs and is used in the MLP of this research. It is described by equation (2.2). Details about other activation functions can be found in [180].

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{2.2}$$

To generalise an ANN and achieve accuracy with input data not seen during the training process, overfitting should be avoided during the training period [181]. "*Overfitting is a phenomenon which indicates that the neural network has too closely approximated/learned, the data examples*" [182]. To avoid overfitting, two methods are reported in [181], [182]: early stopping of training and use of less hidden units (pruning). Early stopping can be achieved by halting the training algorithm when the testing error falls below a predefined threshold [181]. The testing error is calculated in parallel to the training error using a set of testing data. The number of hidden units is generally decided by a trial and error procedure, as there is not yet any proven method to provide the optimum number [183]. In [184], a comparison of methods for defining the architecture of an ANN is provided, with the Hecht-Nielsen's rule, outperforming more modern approaches. This rule was used for the MLP developed in Chapter 5; the hidden neurons are 2N+1, where N is the number of input neurons [185].

The software requirements of the ANN development for the agent that implements load forecasting were:

- Implementation or bridge with JAVA™ language, to be easily incorporated and work online with the proposed MAS.
- Speed and accuracy in online learning/processing data, to enable the use of the proposed system in real-time environment.

Three JAVA™ based neural network software packages, Joone, Neuroph and Encog® were compared in [186]. All three packages were found equally accurate. The open source libraries of Encog® were used for the MLP in this thesis, due to the speed that its algorithms provide [186].

It should be noted that the neural networks for the particular application used in Chapter 5 does not consider cyclic behaviour (similar days) or special event days. Load demand data for two days are used, assuming that these days are the same day of the previous week and the day before the prediction. A larger set of data including weather data could be used to identify similar days in terms of load demand patterns and the data for such days could be used to train the ANN.

2.5 SUMMARY

This chapter reviewed the relevant literature for this thesis. Standards and guidelines related to the EV interaction with the power system were identified.

Studies that have been completed and were related to EV utilisation impact on grid demand, at a national level were reviewed. The modelling assumptions made in each study were discussed.

Studies concerned with the impact of EV battery charging on distribution networks were reviewed. A summary of these studies according to the modelling assumptions, method or software used, the electricity network studied and the aims of each study, was provided.

Aggregation concepts related to coordinated control of Electric Vehicle battery charging were reviewed. Centralised and decentralised control methods were presented. The description of each control method for completed studies was provided. The advantages and disadvantages of each concept were discussed. The application of distributed control methods in power systems was discussed.

The attributes of agents and Multi-Agent Systems were reported. The main components of the Agent Reference Management Model, according to the Foundation of Intelligent and Physical Agents, were described. The elements of the JADE software that was used for the development of the agent based system presented in Chapter 5 were provided. A brief reference was given to artificial neural networks and the characteristics of the particular network type used in the MAS proposed in this thesis.

CHAPTER 3

ELECTRIC VEHICLE BATTERY CHARGING IMPACT ON GRID DEMAND

3.1 INTRODUCTION

The effect of residential charging of Electric Vehicles on electricity demand at a national level is addressed. A study case is defined to investigate how different charging regimes and EV uptake levels will affect the electricity demand of Great Britain in 2030. A comparison with Spain is presented. The aim of this chapter is to provide grid operators with an insight of the anticipated changes in the load profile shape and peak increase or time displacement with EV utilisation.

3.2 EV UPTAKE IN 2030

The number of Electric Vehicles in Great Britain are estimated for the year 2030 using the Business as Usual and Extreme Range scenarios presented in [4] (Table 2.1). These numbers correspond to EV uptake levels for the UK and are referred to in this chapter as low EV uptake and high EV uptake. The total numbers of vehicles for GB and Spain were projected for the year 2030. The projections were made by means of curve fitting using historical data. The R^2 quantity (usually termed coefficient of determination) was used as a measure to evaluate the projections. This quantity stands for the sum of squares of the residuals for a polynomial or exponential fit [187]. It shows how well, the equations which were constructed to express the increase in vehicles, fit with the historical data trend. R^2 values range from 0 to 1, denoting zero and perfect correlation respectively (Equation 3.1).

$$R^2 = 1 - \frac{\sum_i (y - p)^2}{\sum_i (y - \bar{y})^2} \tag{3.1}$$

Where

y is the observed value of the data used for the equation's construction,

p is the predicted value of the data calculated by the constructed equation,

$\bar{y}$ is the mean of the observed data,

i is the number of observed data.

The number of vehicles in the UK was projected to be 42.4 million in 2030 using linear extrapolation with data for the number of vehicles in the UK from 1950 [187]. The population and number of cars in GB was approximately 97% of the whole UK's in 2008 [189], [190]. According to this percentage, the low EV uptake is translated to 7.07% penetration of EVs and the high EV uptake to 48.56% in GB.

The number of vehicles in Spain was estimated for the year 2030, using linear extrapolation with data for the number of vehicles in Spain from 2001 acquired from [191]. In order to make a comparison between GB and Spain, the same low and high EV uptake percentage levels from GB, were used for the Spanish case study. The number and type of EVs used for each take up level, is shown in Table 3.1, together with the value of R^2 for each prediction.

Table 3.1 EV uptake predictions in 2030 by country, level and type of vehicle

Country	**UK (projected)**		**Spain**		**GB (calculated)**	
Vehicle Fleet of 2030 (million)	42.423 (R^2= 0.997)		35.347 (R^2= 0.985)		41.196	
EV fleet of 2030 (million)	**BEVs**	**PHEVs**	**BEVs**	**PHEVs**	**BEVs**	**PHEVs**
Low uptake	0.5	2.5	0.416	2.083	0.485	2.422
High uptake	5.8	14.8	4.832	12.331	5.63	14.33

3.3 STUDY ASSUMPTIONS

According to document [4], EV use is likely to develop first in urban areas and the most common places to charge EV batteries will be residential parking spaces and garages. In the UK, single phase connected domestic plugs, allow the flow of 13A or 16A [4]. 13A single phase connection was assumed to be the main domestic charger rating in GB in 2030. A regulation from the Spanish government, recommends 16A for standard domestic plugs [192] and this value was used in this study. It was assumed that all batteries would be initially at 20% State of Charge (SoC) and then fully charged to a 100%. Table 3.2 shows the main assumptions used in this study.

Table 3.2 EV related assumptions used in Chapter 3

<table>
<tr><th colspan="2">Main assumptions of the study</th><th>Source</th></tr>
<tr><td>EV charger efficiency (%)</td><td>87</td><td rowspan="2">[75], [192]</td></tr>
<tr><td>EV battery charging efficiency (%)</td><td>85</td></tr>
<tr><td colspan="2">EV charger rated power (kW)</td><td rowspan="3">[4], [192]</td></tr>
<tr><td>UK</td><td>2.99</td></tr>
<tr><td>Spain</td><td>3.68</td></tr>
<tr><td colspan="2">Battery capacities (kWh)</td><td rowspan="3">[4], [76]</td></tr>
<tr><td>BEV</td><td>35</td></tr>
<tr><td>PHEV</td><td>9</td></tr>
<tr><td colspan="2">Usable EV battery capacity</td><td rowspan="2">[75]</td></tr>
<tr><td colspan="2">80% of the nominal to ensure long battery life</td></tr>
</table>

The published daily electricity demand profiles from National Grid Company, were used for the GB power system. The demand profiles of 15th day of the first month of each season were used [194]. In document [4], it is assumed that in 2030, the annual UK electricity demand is going to be 390 TWh. Statistics for the UK drawn from [195] show that the energy consumption of Northern Ireland was 2.4% of the whole UK energy consumption in 2006. According to this percentage, it is assumed that the annual electricity demand of GB in 2030 will be 380.6 TWh, a 12% increase from 2008.

The published daily electricity demand profiles from the Spanish National Commission of Energy were used for the Spanish power system [196]. The profiles of the 15th day of the first month of each season were used. The Spanish electricity demand in 2008 was 263.5 TWh according to the TSO of Spain [197]. In a document from the Spanish association of electricity industry [198], the Spanish electricity demand of 2030 is projected to be 428.8 TWh, an increase of 62.7% from 2008. This figure is a projection based on the expected economic growth and historical data of annual electricity demand increases [199].

The demand profiles for GB and Spain were assumed to follow the same patterns in 2030 as in 2008, scaled by 12% for GB and 62.7% for Spain. Fig. 3.1 shows the electricity demand by time of day for the assumed typical days of 2008 and 2030 with data acquired from [197], [200], [201]. The figures for the spring season are omitted due to their close similarity to the autumn season.

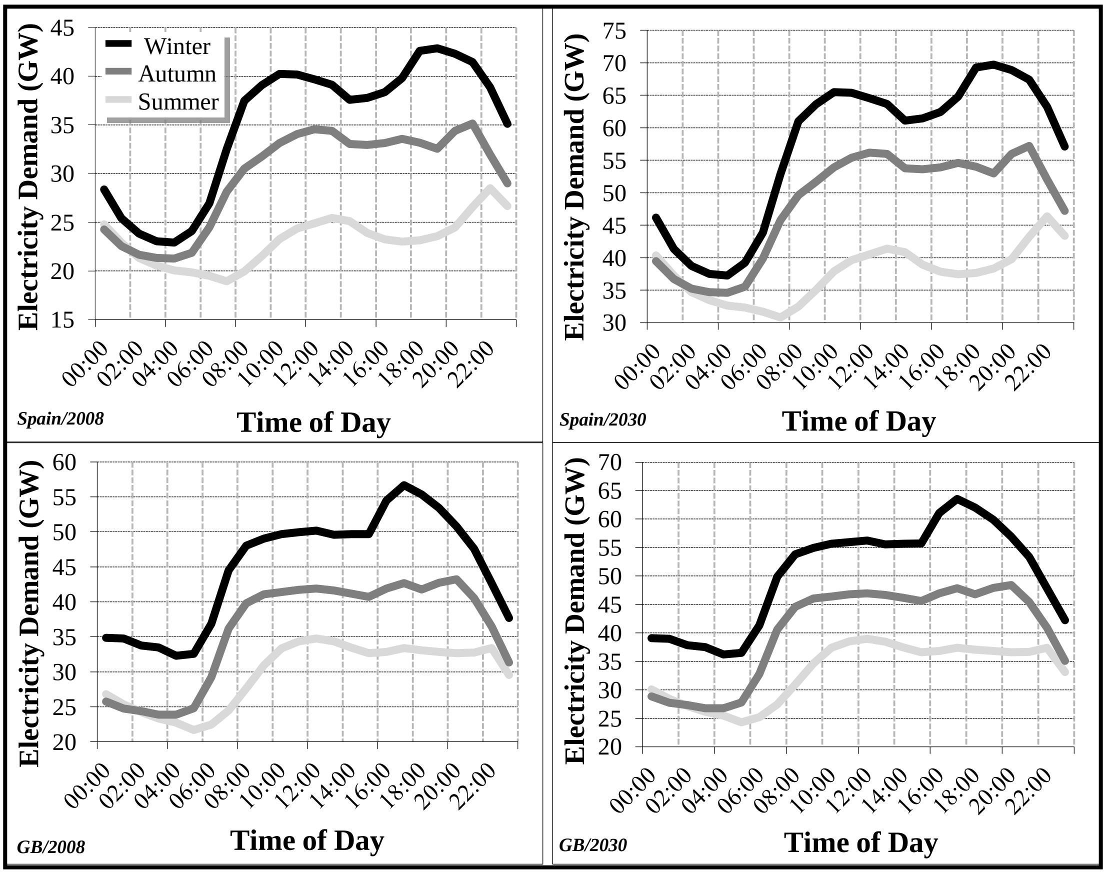


Fig. 3.1 Electricity demand for three seasons of 2008 (actual) and 2030 (projected)

3.4 EV CHARGING REGIMES

Four charging regimes were studied.

3.4.1 Uncontrolled Regime

In the uncontrolled regime, commuters start the EV charging as soon as they return home. The daily traffic pattern of commuters determines the occurrence of EV charging.

The traffic distributions by time of the day for a typical weekday were acquired from the Department of Transport [202] for UK and from the Spanish Ministry of Public Works for Spain [203]. The traffic distribution for GB was considered to be the same as for the UK. The traffic distributions do not assume seasonal variations.

The average time of daily trips in the UK is approximately 20 minutes [204] over the last 30 years. The average daily trip time for GB was considered to be the same as for the UK. It was assumed that each commuter journey within a specific hour will start charging the EV battery in the following hour.

The earliest hour for domestic EV charging in the uncontrolled regime was considered to be 16:00. Traffic distributions and the number of commuters who start the charging of their EVs in each hour are shown in Fig. 3.2.

The batteries would become fully charged from 20% SoC in approximately 4 hours for a PHEV and 15 hours for a BEV in GB. In Spain, a full charge of a PHEV would require 3 hours and a BEV approximately 12 hours, based on the EV charger rating and the Lithium-ion battery characteristics provided in Table 3.2.

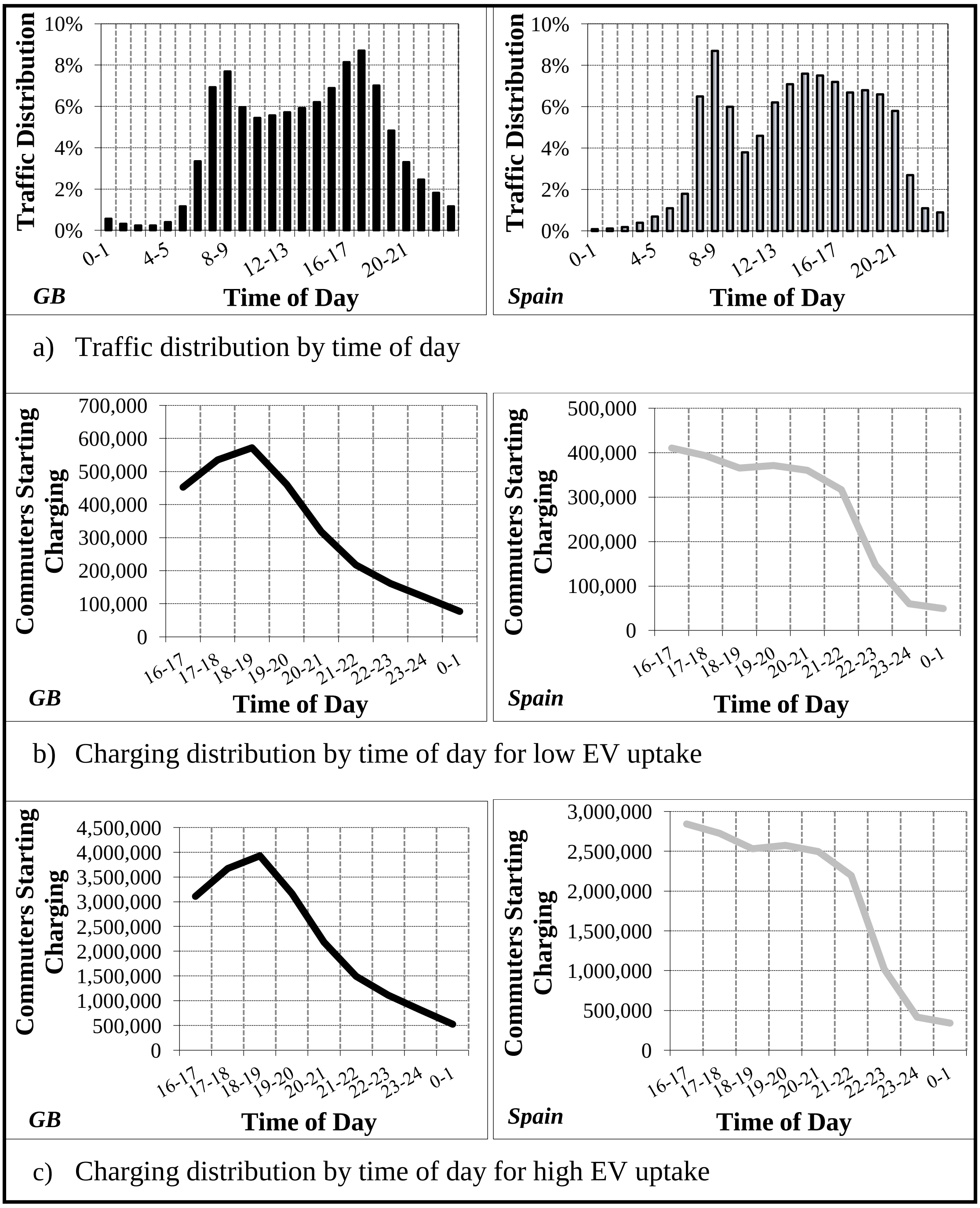


Fig. 3.2 Traffic distributions and number of commuters starting the charging process for uncontrolled case by time of day for low and high EV uptake

3.4.2 Dual Tariff Regime

In the dual tariff regime, the commuters are assumed to charge overnight. In GB, different price rates and off peak times and durations exist, depending on the energy supplier. For simplification, it was assumed that British off peak charges start at 23:00 and finish at 7:00 of the next day's morning, according to [205]. It was assumed that the customers, who return home before 23:00, start their EV charging at 23:00. The EV owners who would return home between 23:00 and 24:00, would start the charging process the hour commencing 24:00. Spanish off peak rates start at 22:00 and finish at 12:00 the following day, according to [206].

3.4.3 Variable Price Regime

In the variable price regime, it was assumed that there will be a wide use of smart meters in 2030. Smart meters were assumed to have a functionality to receive price signals. PHEVs, which would need approximately 4 hours to achieve a full SoC, were assumed to charge during the cheapest hours of the day, following the price signals. The cheapest hours, with respect to electricity market prices, were acquired from [207] for GB and from [197] for Spain. It was assumed that the times of cheapest rates during 2030 would be identical to the cheapest times of 2008. BEVs were considered to fully charge as in the uncontrolled scenario.

3.4.4 Mixed Charging Regime

In the mixed charging regime, the above three regimes were combined:

- One third of the EV owners would charge their EVs using the uncontrolled regime.
- One third of the EV owners would charge their EVs using the dual tariff regime.
- One third of the EV owners would charge their EVs using the variable price regime.

3.5 RESULTS

The effect of EV battery charging on peak demand figures and peak demand times on the national power systems of GB and Spain is evaluated. The peak demand increases and peak time displacements for the low EV uptake case are shown in Table 3.3. Table 3.4 shows the results for the high EV uptake.

Table 3.3 Peak increase and time displacement by season as a result of EV charging and low uptake

Season (GB)	**Actual Peak Time (2008)**	**Uncontrolled Charging**		**Dual Tariff Charging**	
		Peak Increase GW (%)	**Projected Peak Time (2030)**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**
Spring	18:00-19:00	5.770 (11.4%)	19:00-20:00	-	18:00-19:00
Summer	12:00-13:00	3.940 (10.1%)	20:00-21:00	2.653 (6.8%)	23:00-24:00
Autumn	20:00-21:00	6.315 (13%)	20:00-21:00	-	20:00-21:00
Winter	17:00-18:00	3.160 (5%)	18:00-19:00	-	17:00-18:00
Season (Spain)	**Actual Peak Time (2008)**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**
Spring	21:00-22:00	5.337 (10.1%)	21:00-22:00	5.469 (10.3%)	22:00-23:00
Summer	13:00-14:00	4.513 (9.7%)	21:00-22:00	8.664 (18.7%)	22:00-23:00
Autumn	20:00-21:00	5.337 (9.3%)	20:00-21:00	3.487 (6.1%)	22:00-23:00
Winter	20:00-21:00	4.913 (7%)	20:00-21:00	2.146 (3.1%)	22:00-23:00
Season (GB)	**Actual Peak Time (2008)**	**Variable Price Charging**		**Mixed Charging**	
		Peak Increase GW (%)	**Projected Peak Time (2030)**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**
Spring	18:00-19:00	1.179 (2.3%)	18:00-19:00	2.231 (4.4%)	19:00-20:00
Summer	12:00-13:00	-	12:00-13:00	0.560 (1.4%)	20:00-21:00
Autumn	20:00-21:00	1.452 (3%)	20:00-21:00	2.592 (5.3%)	20:00-21:00
Winter	17:00-18:00	1.452 (2.3%)	17:00-18:00	1.460(2.3%)	18:00-19:00
Season (Spain)	**Actual Peak Time (2008)**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**
Spring	21:00-22:00	0.763 (1.4%)	21:00-22:00	2.031 (3.9%)	21:00-22:00
Summer	13:00-14:00	1.518 (3.3%)	22:00-23:00	4.902 (10.6%)	21:00-22:00
Autumn	20:00-21:00	-	21:00-22:00	1.785 (3.1%)	20:00-21:00
Winter	20:00-21:00	1.074 (1.5%)	18:00-19:00	1.642 (2.4%)	20:00-21:00

The results for the EV charging regimes defined in Section 3.4 are graphically shown for two-day duration of each season studied for the year 2030. Spring season results are omitted from the graphs due to their similarity with the results for the autumn season.

The uncontrolled charging regime results (Fig. 3.3 and Fig. 3.4), show that peak demand times coincide with the times that commuters would plug-in their EVs. This would lead to a peak demand increase for all seasons and both countries.

Table 3.4 Peak increase and time displacement by season as a result of EV charging and high uptake

Season (GB)	Actual Peak Time (2008)	Uncontrolled Charging		Dual Tariff Charging	
		Peak Increase GW (%)	**Projected Peak Time**	**Peak Increase GW (%)**	**Projected Peak Time**
Spring	18:00-19:00	41.216 (81.6%)	19:00-20:00	49.256 (97.5%)	00:00-01:00
Summer	12:00-13:00	40.989 (101%)	20:00-21:00	52.41 (134.5%)	23:00-24:00
Autumn	20:00-21:00	43.364 (89.5%)	20:00-21:00	44.916 (92.7%)	23:00-24:00
Winter	17:00-18:00	37.872 (59.6%)	19:00-20:00	36.967 (58.2%)	23:00-24:00
Season (Spain)	**Actual Peak Time (2008)**	**Peak Increase GW (%)**	**Projected Peak Time**	**Peak Increase GW (%)**	**Projected Peak Time**
Spring	21:00-22:00	41.64 (79%)	21:00-22:00	59.110(112.1%)	22:00-23:00
Summer	13:00-14:00	38.73 (83.5%)	21:00-22:00	60:303(130%)	22:00-23:00
Autumn	20:00-21:00	41.641(72.8%)	21:00-22:00	55.126(96.3%)	22:00-23:00
Winter	20:00-21:00	41.325 (56.4%)	20:00-21:00	53.785(77.1%)	00:00-01:00
Season (GB)	**Actual Peak Time (2008)**	**Variable Price Charging**		**Mixed Charging**	
		Peak Increase GW (%)	**Projected Peak Time**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**
Spring	18:00-19:00	45.393 (89.8%)	03:00-04:00	19.03 (37.6%)	20:00-21:00
Summer	12:00-13:00	46.99 (120.6%)	03:00-04:00	24.78 (63.6%)	22:00-23:00
Autumn	20:00-21:00	39.113 (80.7%)	01:00-02:00	17.29 (35.7%)	23:00-00:00
Winter	17:00-18:00	38.544 (60.7%)	23:00-24:00	10.21 (16.1%)	20:00-21:00
Season (Spain)	**Actual Peak Time (2008)**	**Peak Increase GW (%)**	**Projected Peak Time**	**Peak Increase GW (%)**	**Projected Peak Time (2030)**
Spring	21:00-22:00	50.489(95.7%)	03:00-04:00	29.82 (56.6%)	22:00-23:00
Summer	13:00-14:00	50.188(108.2%)	05:00-06:00	33.01 (71.2%)	21:00-22:00
Autumn	20:00-21:00	41.136(71.9%)	02:00-03:00	27.83 (48.7%)	22:00-23:00
Winter	20:00-21:00	29.504(41.1%)	05:00-06:00	27.49 (38.1%)	23:00-24:00

The dual tariff regime results for the low EV uptake scenario (Fig. 3.5 and Fig. 3.6), show that peak demand times would be shifted to the time when off peak charges start. In GB, for the low EV uptake case, increase in demand was observed only during the summer season. Regarding Spain and the low EV uptake, peak demand was increased for every studied season.

The variable price charging results for the low EV uptake scenario (Fig. 3.7 and Fig.3. 8), show that EV battery charging tends to fill the night valley of the load curve, as the cheapest hours for every season and both countries would occur during minimum demand times.

The mixed charging results for the low EV uptake scenario (Fig. 3.9 and Fig. 3.10), show that peak demand times would coincide with the peak demand times of the uncontrolled regime.

3.6 DISCUSSION OF THE RESULTS

The maximum simultaneous demand served in GB during the winter of 2008 was 60.3GW [208]. This is forecasted to increase by 12% in 2030 [4] raising the figure to 67.5GW. The low EV uptake case for uncontrolled charging in GB, was projected to increase the winter typical day peak demand by 3.2GW, raising the maximum simultaneous demand to 70.7GW in 2030. The GB generating capacity in 2030 is projected to be 120GW [4], with renewable generation holding 32% of the total generating capacity. The load factor of the 2008 GB generation system was 67% [209]. In order to supply the increased demand from low EV uptake, the generation system load factor should not decrease below 59%.

The maximum simultaneous demand served in Spain during the winter of 2008 was 42.9GW [210]. The projected increase in demand by 62.7% in 2030 [198], would raise the maximum simultaneous demand to 69.9GW. The low EV uptake case for uncontrolled charging in Spain, was projected to increase the winter typical day peak demand by 5.1GW, raising the maximum simultaneous demand to 75GW. The Spanish generating capacity in 2030 is projected to be 107.8GW [210], with renewable generation holding approximately 40% of the total generating capacity. The load factor of the 2008 Spanish generation system was 65.56% [198]. In order to supply the increased demand from low EV uptake, the generation system load factor should increase to 69%.

The effect of a price based charging control type on electricity demand was investigated. In this control type, namely variable price charging, the charging of PHEVs occurred during the cheapest hours of the day. This type of control resulted in peak demand reductions, compared to the uncontrolled scenario for the low EV uptake. The typical winter day electricity demand peaks were reduced by 2.5% for GB and 5.4% for Spain.

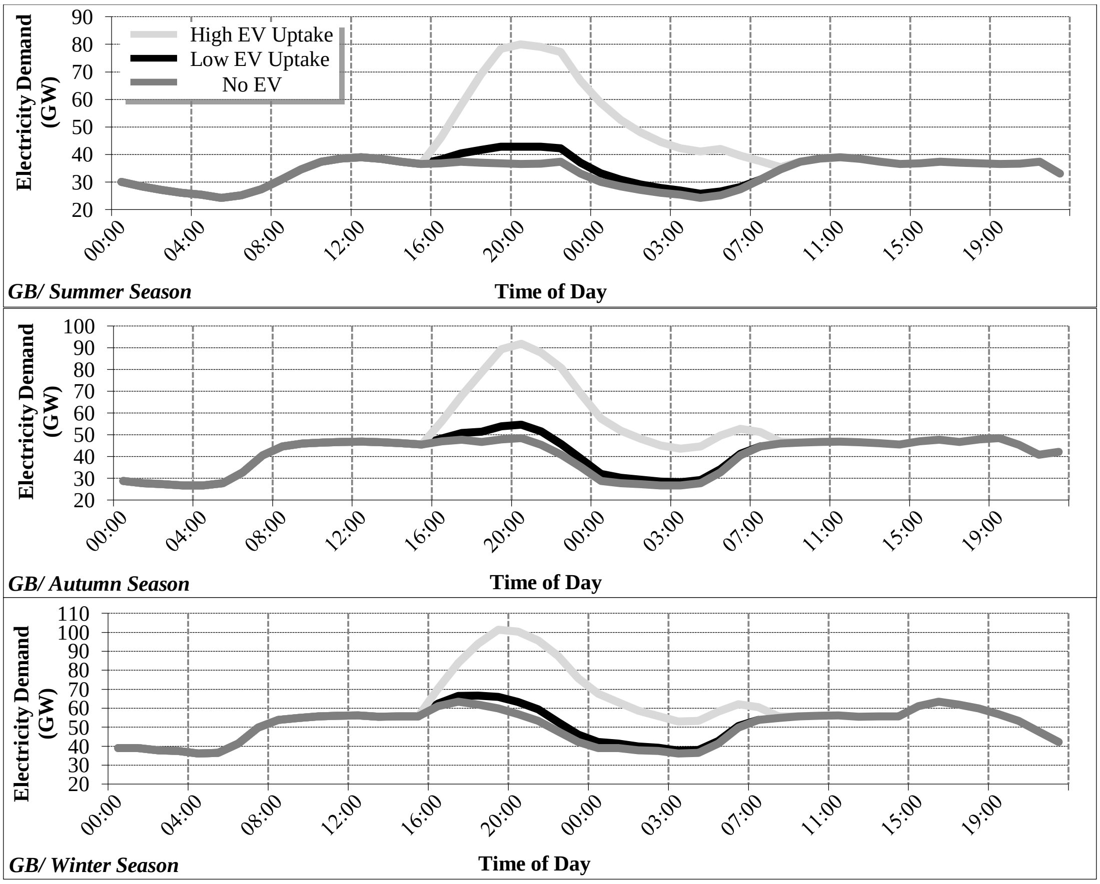


Fig. 3.3 British predicted energy demand for uncontrolled charging in 2030

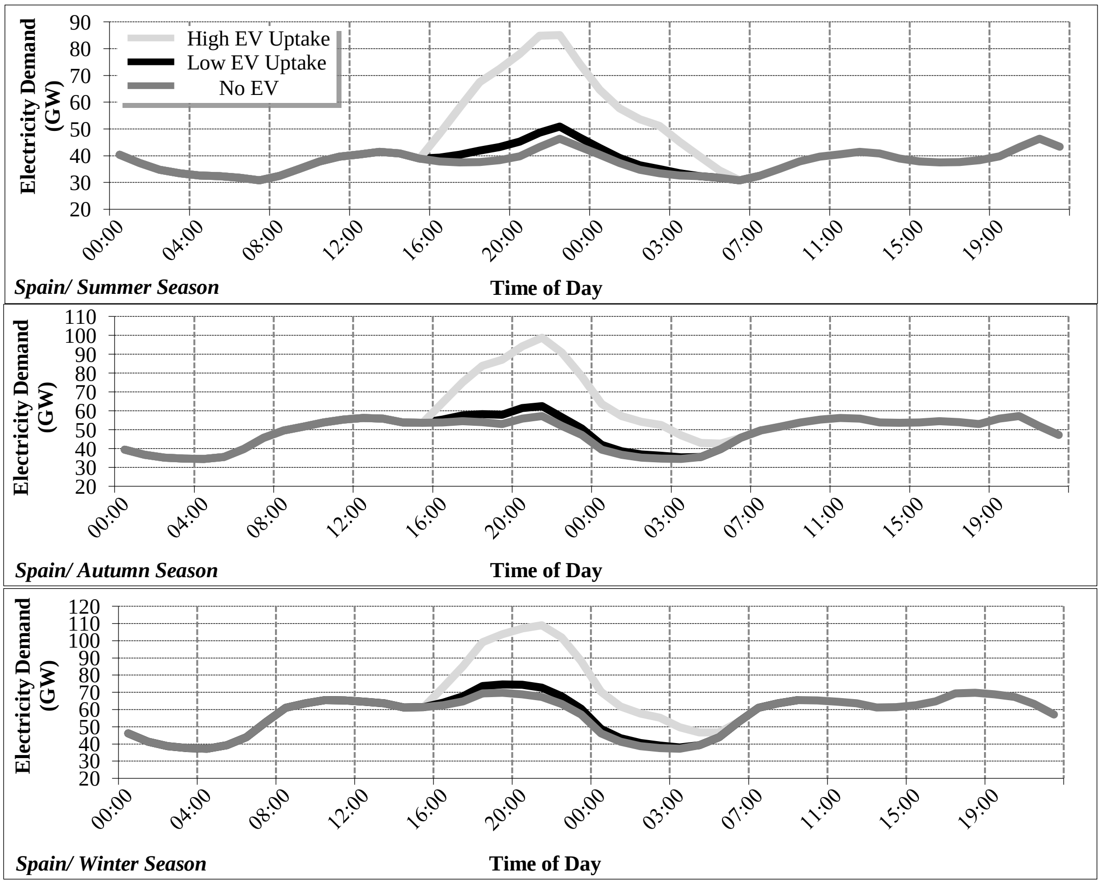


Fig. 3.4 Spanish predicted energy demand for uncontrolled charging in 2030

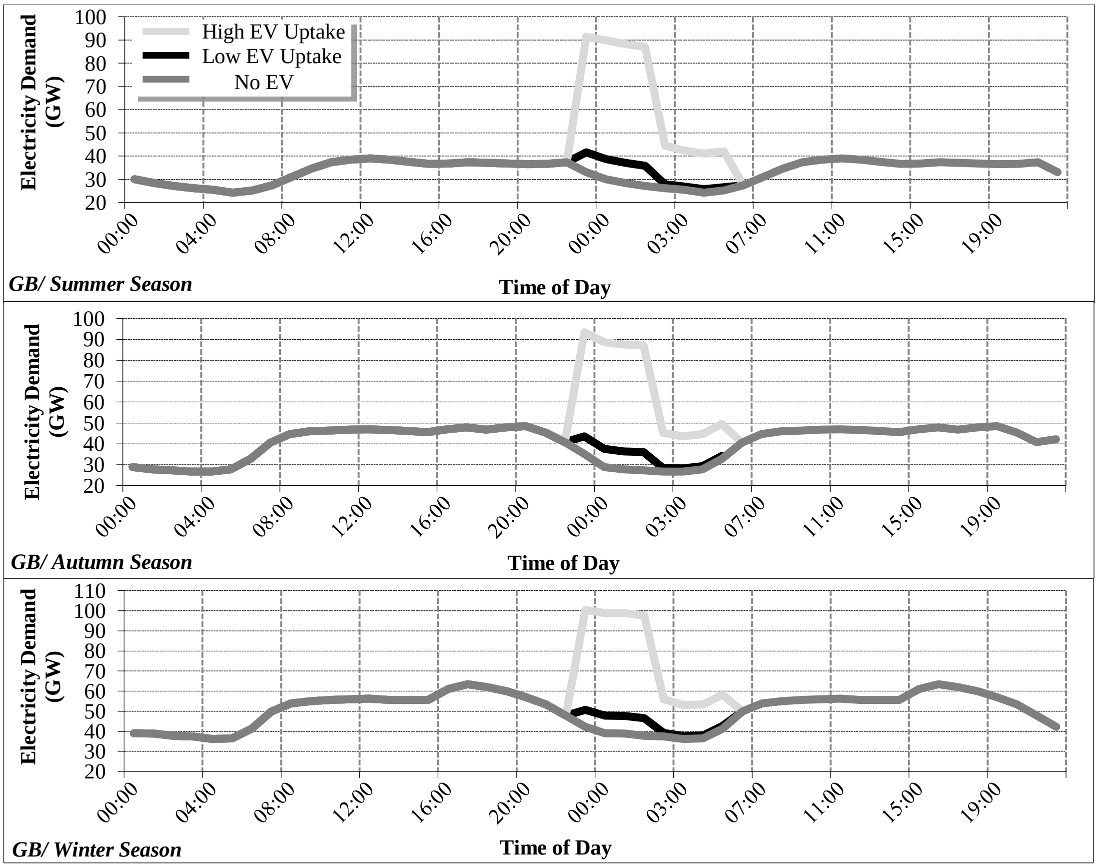


Fig. 3.5 British predicted energy demand for dual tariff charging in 2030

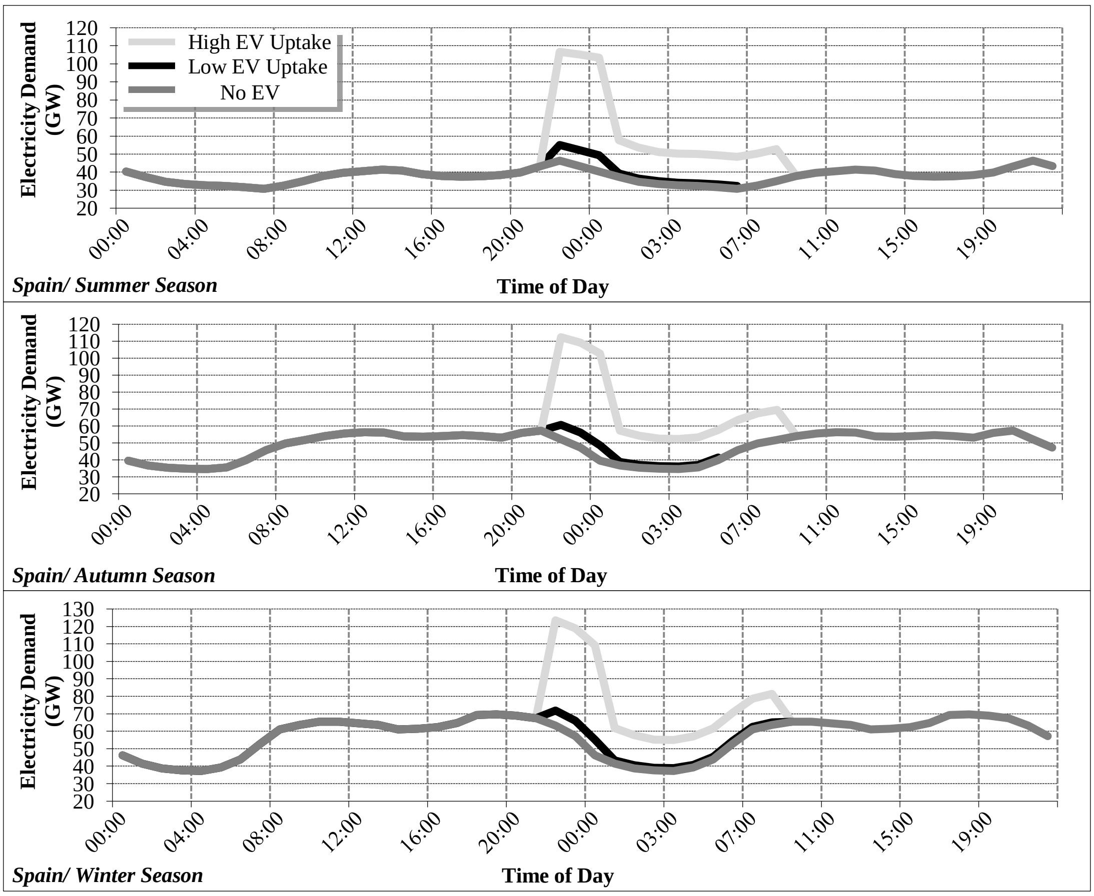


Fig. 3.6 Spanish predicted energy demand for dual tariff charging in 2030

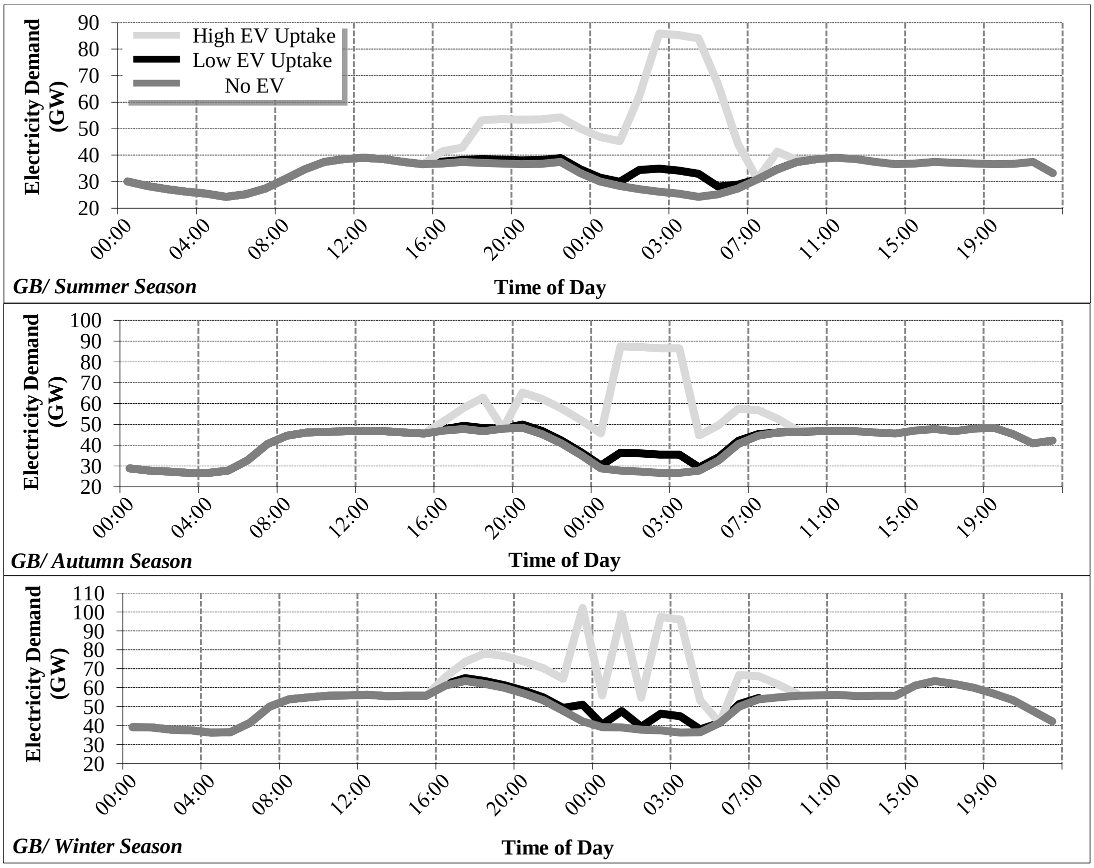


Fig. 3.7 British predicted energy demand for variable price charging in 2030

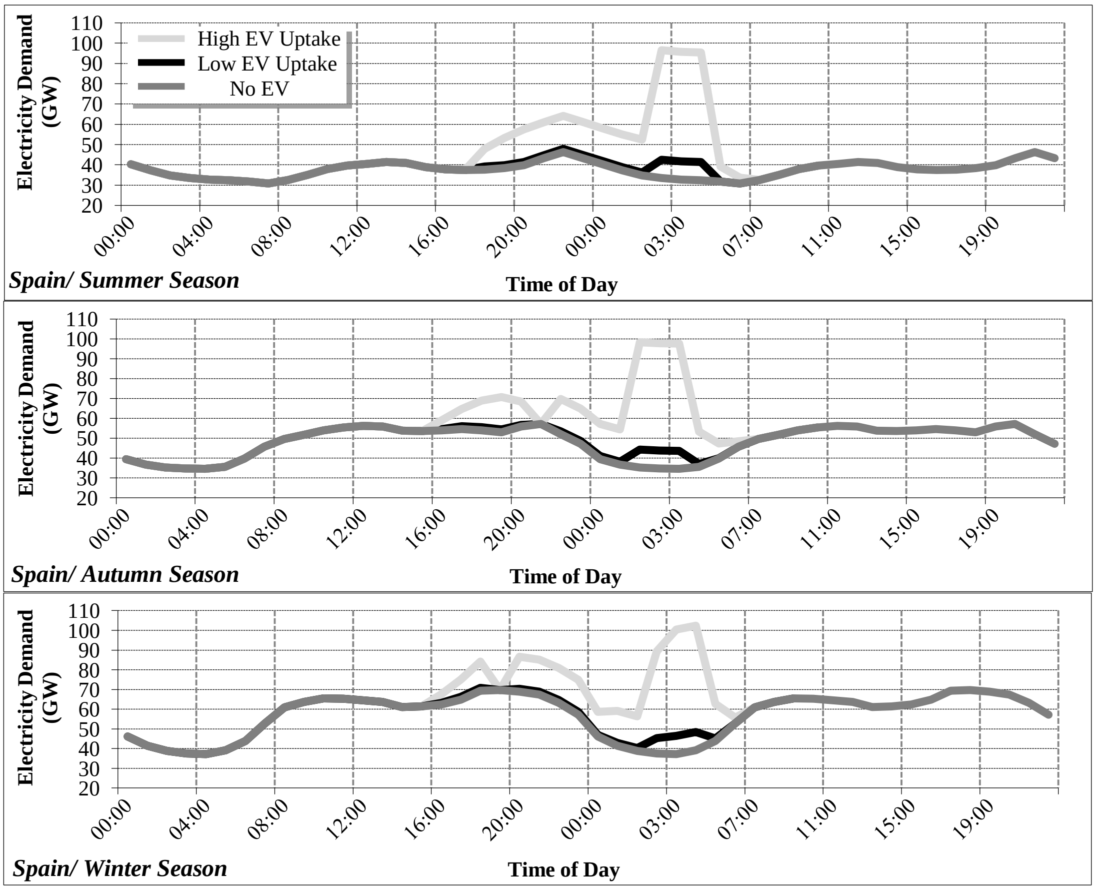


Fig. 3.8 Spanish predicted energy demand for variable price charging in 2030

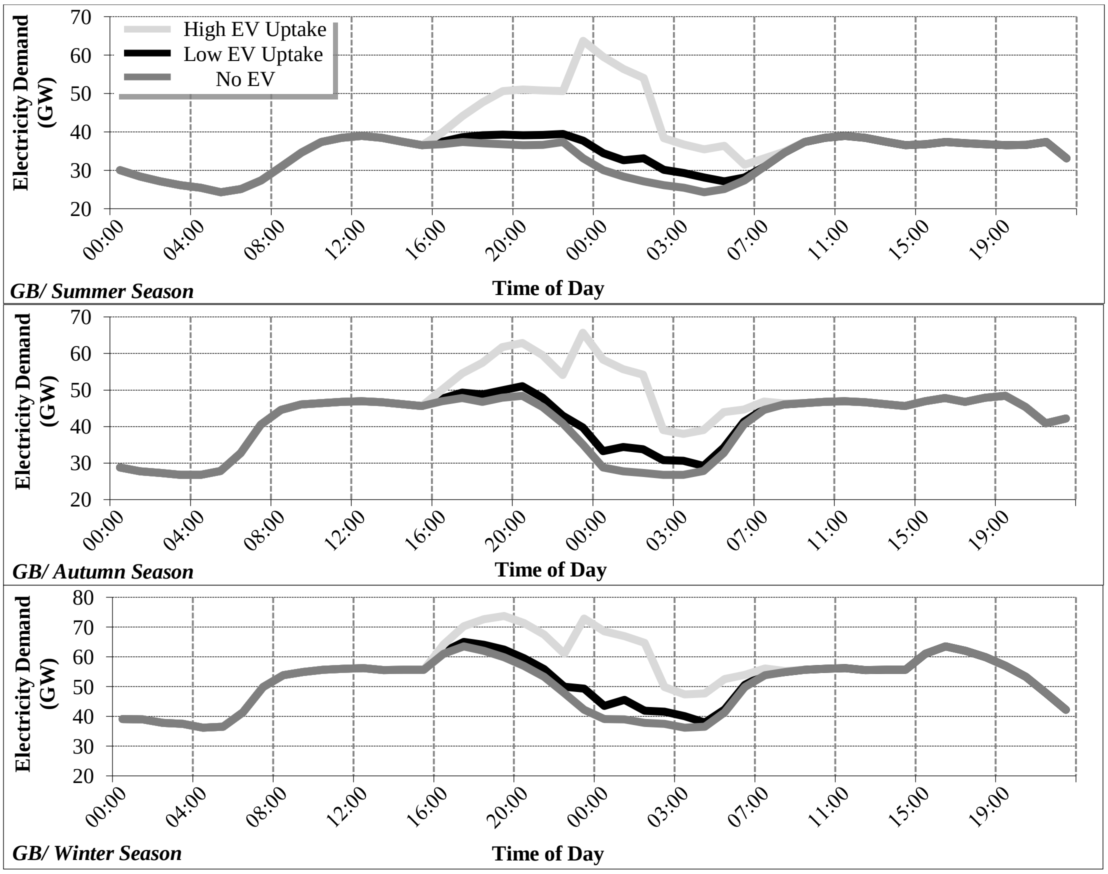


Fig. 3.9 British predicted energy demand for mixed charging in 2030

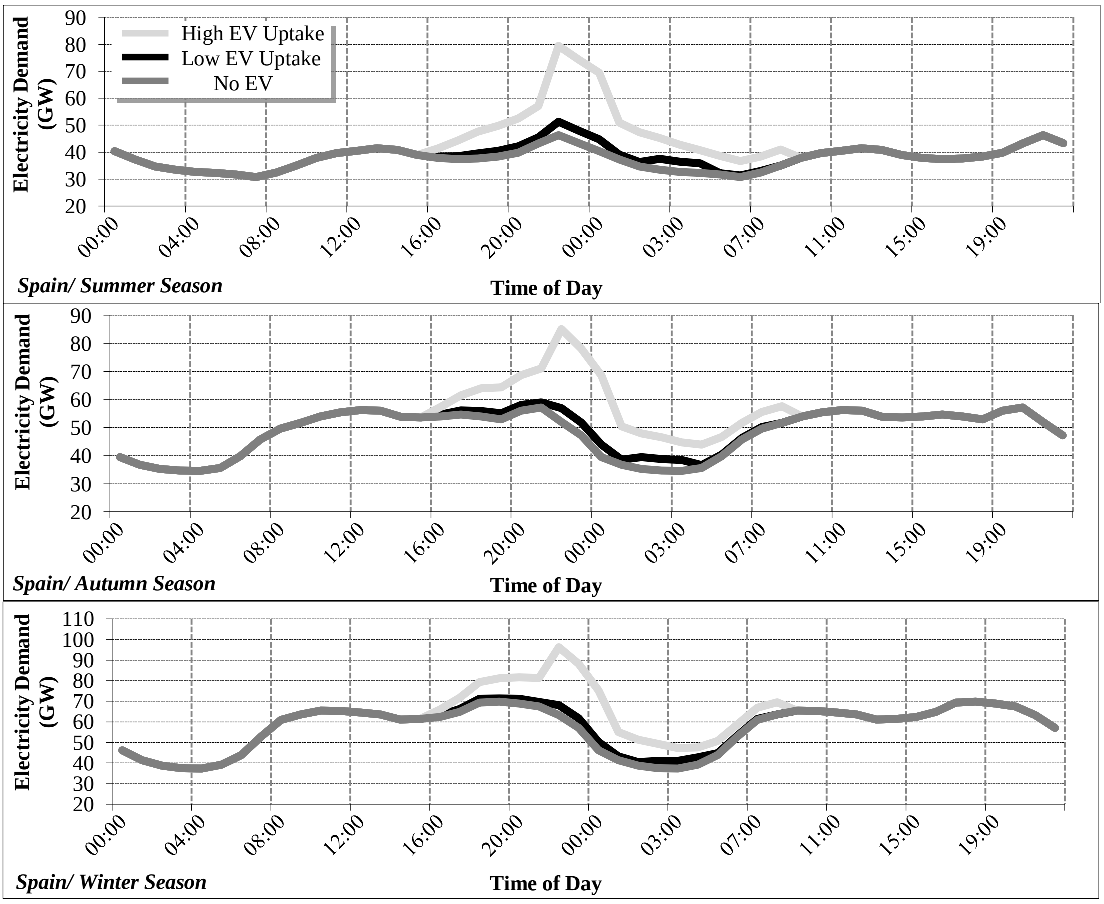


Fig. 3.10 Spanish predicted energy demand for mixed charging in 2030

3.7 Summary and Comparison with Relevant Studies

The impact of domestic charging of electric vehicles' batteries on the electricity demand of Great Britain and Spain was examined. A study case was created to investigate how different charging regimes and EV uptake levels will affect the electricity demand of both power systems. The peak demand increase for each charging regime and each country are summarised in Fig. 3.11.

The results for low EV uptake show that the increase in demand peaks could be managed with a dual tariff and dynamic price control. Low EV uptake, equivalent to 7% of the whole car fleet, would increase the typical day electricity demand peaks:

- Uncontrolled EV charging was found to increase the British winter day peak demand by 3.2GW (3.1%) and the Spanish winter day peak demand by 4.9GW (7%).
- Dual tariff control would not affect the British winter day peak. The Spanish winter day peak demand would be increased by 2.1GW (3.1%).
- Variable price control would increase the British winter day peak demand by 1.5GW (2.3%) and the Spanish winter day peak demand by 1.1GW (1.5%).
- Mixed charging would increase the British winter peak demand by 1.5GW (2.3%) and the Spanish winter day peak demand by 1.6GW (2.4%).

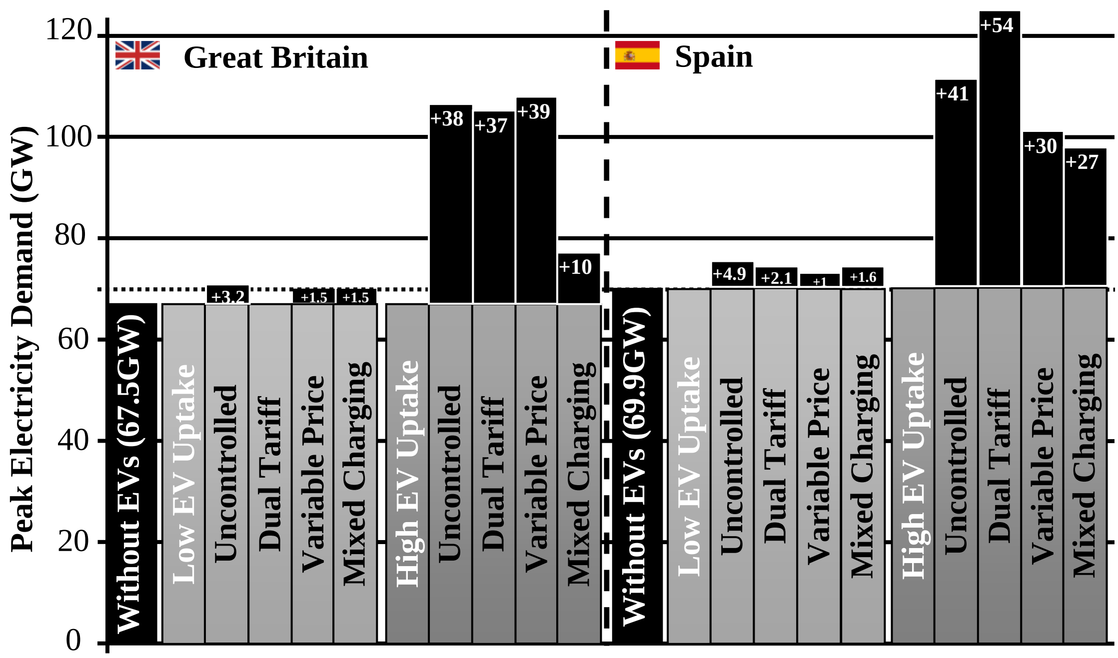


Fig. 3.11 Electricity demand peak increase in winter of 2030 from EV battery charging in GB and Spain

In MERGE project [78], a 10% EV uptake (of 2009 car fleet) was used to examine the effect on peak demand on British and Spanish systems. The results for the uncontrolled charging regime of the present study and study [78] are compared in Table 3.5. The comparison shows that the peak demand times are identical in both studies. The traffic pattern assumptions used in the present study coincide with the results of the survey conducted in [78]. The difference in peak demand figures is due to the difference in number of EVs used in each study.

Table 3.5 Comparison of the results between the present study and the European project's MERGE

Winter Peak Demand Increase and Time Displacement		
Country	*Present study*	*MERGE project* [78]
GB	3.160 GW (5%) at 18:00	5.596 GW (8%) at 18:00
Spain	4.913 GW (7%) at 20:00	4.033 GW (7%) at 20:00

In a study published by researchers from the Caledonian University of Glasgow [77], a 10% EV uptake (of 2008 car fleet) was used to examine the effect on peak demand on the British system. Three types of EVs with an equal number of battery charging characteristics were simulated to charge within uncontrolled, off-peak and real-time pricing charging regimes. The results of the present study and study [77] for the winter season are compared in Table 3.6.

The comparison between the present study and study [77] shows that:

- For the uncontrolled regime, the peak demand times are identical. The difference in peak demand figures is due to the difference in number of EVs used in each study and the power rating of the chargers.
- For the off-peak regime, grid demand peaks are not affected in the present study in which off-peak times start at 22:00, whereas the peak is increased in study [77] in which off-peak times start at 21:00.
- For the variable price regime, the use of a low power rating charger of 2.99kW assumed in the present study (Table 3.2) would require energy from the grid during a longer period, including the actual peak time. The use of higher power rating EV chargers in study [77] showed that the demand for EV battery charging would be satisfied during the valley hours and hence the actual demand peaks would not be affected.

The high EV uptake case, equivalent to 48.5% of the whole car fleet, will greatly increase the electricity demand daily peaks, irrespectively of the charging regime.

- Uncontrolled EV charging would increase the British winter day peak by 38GW (59.6%) and the Spanish winter day peak by 41GW (56.4%).
- Dual tariff charging would increase the British winter day peak by approximately 37GW (58.2%) and the Spanish winter day peak by 54GW (77.1%).
- Variable price charging would increase the British winter day peak by approximately 39GW (60.7%) and the Spanish winter day peak by 29GW (41.1%).
- Mixed charging would increase the British winter peak demand by 10.21GW (16%) and the Spanish winter day peak demand by 27GW (38%).

Table 3.6 Comparison of the results between the present study and study [77]

Winter Peak Demand Increase and Time Displacement		
Charging Regime	*Present study*	*Study [77]*
Uncontrolled	5% at 18:00	10% at 18:00
Dual Tariff (Off-Peak in [77])	-	6.1% at 21:00
Variable Price (Smart Charging in [77])	2.3% at 17:00	-

CHAPTER 4

ELECTRIC VEHICLE BATTERY CHARGING IMPACTS ON DISTRIBUTION NETWORKS

4.1 INTRODUCTION

The impact of EV battery charging on distribution networks is investigated. A case study is defined for the year 2030. The effect of EV battery charging on a UK generic distribution network's steady-state operating parameters is evaluated.

EV uptake estimates for the year 2030 in terms of penetration per LV residential area are provided.

A deterministic approach is used to evaluate the impact of EV battery charging on steady-state thermal loadings, voltage profiles and power losses of distribution feeders of the UK generic distribution network. A case study for the year 2030 is analysed. Network reinforcement options are evaluated.

A probabilistic approach is used to address distribution network loading uncertainties. The algorithm of a dedicated software tool developed to perform simulations is described. A case study for the year 2030 is analysed and the impact of EV battery charging on steady-state thermal loadings, voltage profiles and power losses of distribution feeders of the UK generic distribution network is evaluated. A set of Graphical User Interfaces (GUIs) that were developed to enable easiness in the insertion of the user defined inputs is shown in Appendix B.

The results of the deterministic and probabilistic approaches are compared and conclusions are drawn.

4.2 CASE STUDY RESIDENTIAL UK GENERIC NETWORK

The typical urban UK distribution network's topology [211] used in this study consists of a HV/MV primary substation feeding a MV network. A 500 MVA three phase 33kV ideal voltage source was used to represent the upstream grid. According to reference [211], this source is connected to two 33/11.5kV 15MVA transformers, an 11kV substation and six 11kV outgoing feeders. Each feeder supplies eight secondary MV/LV substations with an equal number of 11/0.433kV transformers. One feeder was modelled in detail while the remaining feeders were simplified as lumped loads. From each secondary substation, four outgoing radial feeders serve 96 single-phase customers each. The single-phase connections were distributed evenly across the three phases. One feeder was modelled in detail and the remaining feeders were simplified as lumped loads. The network details can be found in [211]. Fig. 4.1 shows the network schematic. The UK generic network parameters were given as inputs to a load flow algorithm for the studies conducted for this chapter. A Newton-Raphson load flow algorithm developed at Cardiff University by a colleague PhD student was used [212].

4.3 EV UPTAKE LEVELS ESTIMATES

The presence of EVs in British LV residential areas for the year 2030 is estimated. Data for UK number of households from 1970 to 2020 were drawn from [213]. Linear extrapolation of these data shows that the number of households in the UK in 2030 will be 30.5 million (Fig. 4.2). The low and high EV uptake levels of Table 3.1 are 12.5% and 70.8% according to the number of households. A medium EV uptake is defined as 33%. Table 4.1 shows these levels and the absolute numbers per 384 customers.

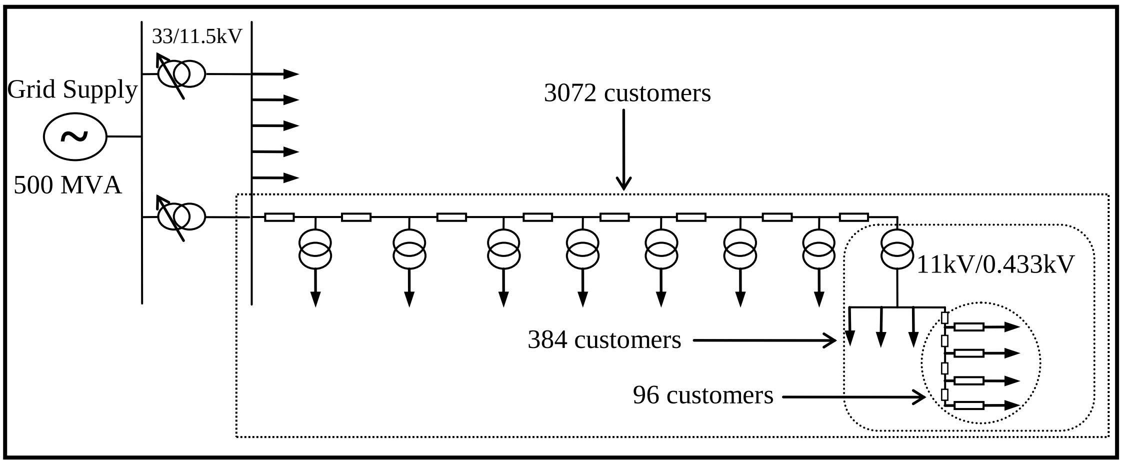


Fig. 4.1 UK LV generic distribution network schematic [211]

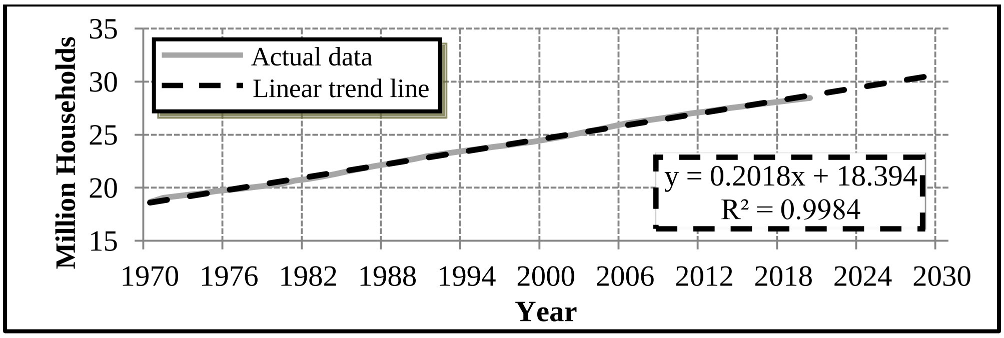


Fig. 4.2 Number of households in the UK

Table 4.1 Estimated EV uptake levels per 384 households in the UK in 2030

EV Type	Low Level	Medium Level	High Level
BEV (units)	16	32	80
PHEV (units)	32	96	192
Total (units)	48	128	272
Total (%)	12.5	33.3	70.8

4.4 DETERMINISTIC STUDY

4.4.1 Assumptions

The operating limits of steady state voltage, distribution transformer and cable loading are drawn from the literature.

4.4.1.1 Voltage

DSOs are obliged to supply their customers at a voltage within specified limits. In the UK, these limits are +10% and -6% from the nominal single phase voltage of 230V, according to the Electricity Safety, Quality and Continuity Regulations [214].

4.4.1.2 Transformer Loading

Transformer loading conditions are determined by the maximum temperature of the transformer's winding [215]. In document [216], it is reported that the temperature of this spot should not exceed 110 ^{0}C. The American National Standards Institute (ANSI) /IEEE C57.91:1981 standard suggests that the transformer loading should be subject to the ambient temperature with reference to 30 ^{0}C [217]:

- For each ^{0}C above 30 ^{0}C, the loading capability drops by 1.5% of the rated kVA.
- For each ^{0}C below 30 ^{0}C, the loading capability increases by 1% of the rated kVA.

The mean winter temperature in the UK during 2009 was 3.2 ^{0}C and the mean summer temperature 14.8 ^{0}C [218]. On average, a 500kVA outdoor distribution transformer would therefore be able to withstand 26.8% overload during winter (134 kVA) and 15.2% (76kVA) overload during summer.

4.4.1.3 LV Underground Cables

LV underground cables in the UK are rated taking into account the following parameters: soil resistivity, ground ambient temperature, maximum conductor temperature, cyclic and distribution rating, ducts and maximum lengths without de-rating and short-circuit rating requirements [219].

DSOs in the UK employ different methodologies for determining the thermal limits that cables can withstand. Publicly available documents from UK DSOs were reviewed. In reference [220], it is reported that sustained and cyclic ratings are used to determine cable thermal limits. In document [221], it is mentioned that only continuous ratings are used to determine cable thermal limits. In reference [222], it is reported that all UK DSOs are collaborating to develop a common tool that will be used to determine the rating of distribution networks' cables.

Load flow simulations performed using the UK generic network of Fig. 4.1, with maximum load data acquired from the Electricity Association [211], showed that the most vulnerable cable is the 185mm^2 cable emanating from the LV busbar supplying 96 customers. Table 4.2 shows the sustained ratings of the 185mm^2 cable from two DSOs [220], [221], the standard BS5467:1989 from [223], and a cable supplier [224]. The lowest of the four values was used as the cable thermal limit (347A).

4.4.1.4 EV Load Modelling

The maximum equivalent load of an EV is determined by the power rating of the charger. In a survey published by the UK Society of Motor Manufacturers and Traders in 2010 [225], it is reported that 20% of the EVs have been designed to be charged by a 3-phase 32A supply, 5% by a 3-phase 16A supply, 5% by a 1-phase 32A supply, 55% by a 13A/16A 1-phase supply and the rest by other types.

Table 4.2 Sustained current carrying capacity (A) of 185mm^2 underground cable

Size (mm^2)	DSO1	DSO2	BS5467:1989	Cable Supplier
185	369	355	347	355

In the UK, the 1-phase 3-pin domestic-style sockets certified against the standard BS1363 are rated 13A [226]. It was assumed that the distribution of EV chargers among EV owners will be 20% 3-phase 32A, 10% 1-phase 32A and the remaining 70% will be 1-phase 13A.

The EVs and the EV chargers were assumed to be uniformly distributed among the network nodes with an equal number of EVs and chargers owned by every customer. In the UK generic distribution network there are 24 customers per network node of the LV feeder. The EV equivalent loads were modelled as purely resistive with constant power. The number of cases that can be studied with non-uniform distribution of EVs and chargers is very large. For this reason, the study of non-uniform distribution of EVs and chargers was considered in the probabilistic approach in Section 4.5. In the probabilistic approach, the location of EVs and chargers was considered to be an uncertain variable.

4.4.1.5 Residential Load Modelling

Minimum and maximum demand figures acquired from the Electricity Association were used to model the minimum and maximum residential loads [211]. These figures correspond to 0.16kW and 1.3kW per customer in 2003 and denote minimum summer values and maximum winter values, respectively. An annual increase of 1% was considered from 2003 to 2030 [220]. The loads were modelled as purely resistive with constant power [211].

4.4.2 Simulation Results for the Steady State Load Flow Deterministic Studies

The impacts on steady state voltage of the LV detailed feeder, distribution transformer loading, and 185mm^2 cable loading, are presented. The electrical power losses that would occur in the cables of the LV feeder are shown for each case investigated.

4.4.2.1 Voltage

Under minimum load conditions of a summer season, voltage was found to violate the lower limits only for the high EV uptake level. Under maximum load conditions of a winter season, the lower voltage limit was violated for medium and high EV uptake levels. The voltage profile of the 96 customers LV feeder is shown for both loading conditions in Fig. 4.3.

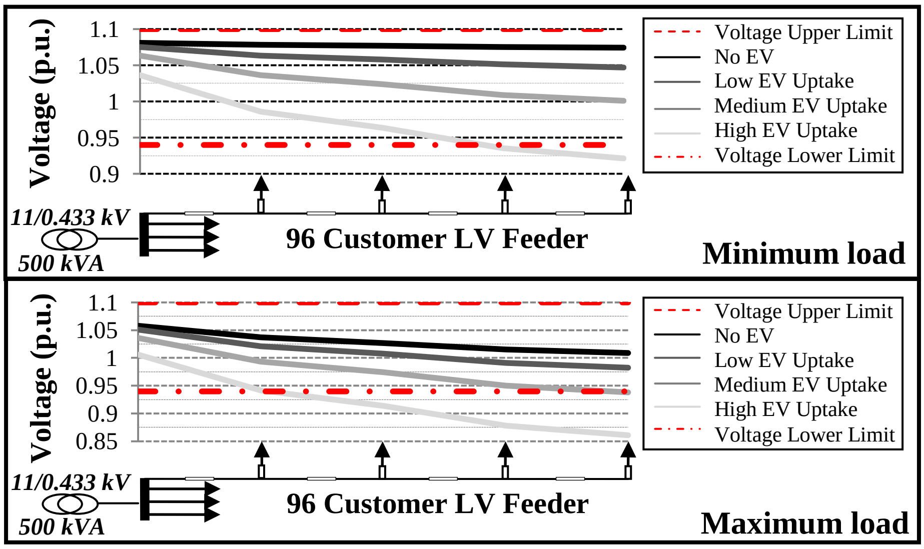


Fig. 4.3 Steady-state voltage profile of LV feeder for different levels of EV uptake

4.4.2.2 Transformer Loading

The distribution transformer was found to be overloaded for the medium and high EV uptake levels under minimum load conditions. Under maximum load conditions, the transformer was overloaded for all EV uptake levels. Table 4.3 contains the transformer loading results.

4.4.2.3 185mm^2 LV Underground Cable

The 185mm^2 cable would exceed the sustained current carrying capacity for the medium and high EV uptake cases under maximum load conditions. Under minimum load conditions the capacity limit would be breached only for the high EV uptake. Table 4.3 shows the simulation results.

Table 4.3 Steady state load flow results for distribution transformer and 185mm^2 cable loading measurements

EV Uptake	Distribution Transformer (kVA)	LV Feeder's 185mm^2 Cable (A)
Minimum Load Conditions During Summer Season		
No EV	93.7	31.1
Low	411.14	135.6
Medium	916.2	299
High	1738	565
Maximum Load Conditions During Winter Season		
No EV	724.2	240
Low	1022	334.5
Medium	1469	482.5
High	2190	718

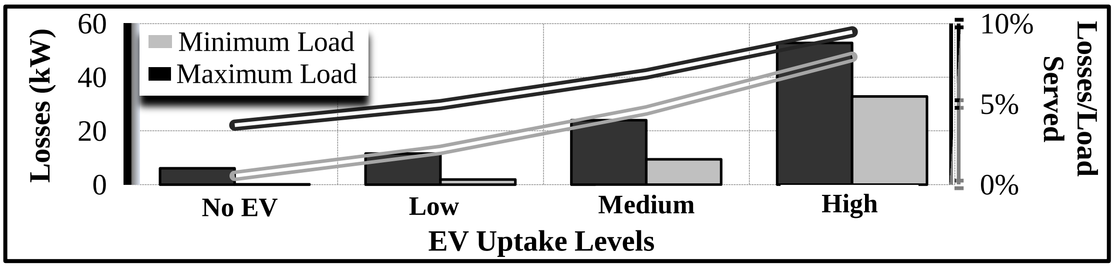


Fig. 4.4 Electrical line losses and losses/load served in the LV feeder

4.4.2.4 Power Line Losses

The electrical losses in the cables of the LV feeder supplying 96 customers were recorded for all simulated cases. An increase in losses is shown as the EV uptake increases (Fig. 4.4). The fraction of losses/load served for the high EV uptake in 2030 (represented as lines in Fig. 4.4), reached 8% under minimum loading conditions and 9% under maximum load conditions.

4.4.2.5 Impact Evaluation with Distribution Network Reinforcements

The impact from EV battery charging on distribution transformer, cable loading, voltage and losses is evaluated assuming that the network would be reinforced. The studied network is tapered with the LV feeder that supplies 96 residences comprising 150 metres of 185mm^2 underground cable followed by 150 metres of 95mm^2 underground cable. Four network upgrade cases are defined. One case with penetration of micro-generation is considered.

- Case 1: The LV feeder is uniform, i.e. the LV feeder comprises 300m of 185mm^2 cable.
- Case 2: The LV feeder is uniform as in Case 1 and the distribution transformer is upgraded to 1MVA.
- Case 3: The first 150m of the 185mm^2 cable are upgraded to 300mm^2, the rest 150m remain to 185mm^2, and the distribution transformer is 1MVA. The sustained current rating of the 300mm^2 cable during winter season is 484A, according to [219].
- Case 4: The first 150m of the 185mm^2 cable are upgraded to 300mm^2, the rest 150m remain to 185mm^2 as in Case 3, and the distribution transformer is upgraded to 2.5MVA.
- Case 5: Each customer owns a micro-generator with an average power rating of 1.1kW according to [211]. The equipment upgrades of Case 4 are applied. Each micro-generator is modelled as a negative load.

The five cases were evaluated with maximum load conditions to consider the most onerous circumstances. The results for the most remote node's voltage, transformer loading, cable loading, losses and losses/load served are shown in Table 4.4. The base case in Table 4.4 repeats the case without network reinforcements for easier interpretation of the results.

The results for the low EV uptake show that the transformer upgrade to a rating of 1.5MVA would be sufficient to satisfy the constraints studied. The results for the medium EV uptake show that when all upgrades were considered (Case 4), the only constraint not satisfied was the loading of the cable emanating from the LV busbar. The application of micro-generators (Case 5) eliminated this constraint.

Table 4.4 Steady-state load flow results for the studied impacts with network reinforcement under maximum loading conditions

Case	Voltage (p.u.)	Transformer Loading (kVA)	Cable Loading (A)	Losses (kW)	Losses/Load Served (%)
Low EV Uptake					
Base Case	0.9826	1.022	334.5	11.53	4.95
Case 1	0.9946	1016	336.1	10.31	4.43
Case 2	1.005	1037	339.6	10.78	4.63
Case 3	1.017	1040	343	8.34	3.58
Case 4	1.019	1045	344	8.35	3.59
Case 5	1.042	576.2	191.3	2.69	1.15
Medium EV Uptake					
Base Case	0.938	1469	482.5	23.99	6.88
Case 1	0.9549	1471	485.7	22.01	6.32
Case 2	0.9728	1526	494.7	22.73	6.53
Case 3	0.9896	1531	502.2	17.83	5.12
Case 4	0.9931	1542	504.2	18.03	5.17
Case 5	1.017	1089	358	17.86	5.12
High EV Uptake					
Base Case	0.8599	2190	717.5	52.9	9.5
Case 1	0.8847	2194	726	50.1	9
Case 2	0.9167	2357	752	52.3	9.4
Case 3	0.9411	2368	770	41.5	7.4
Case 4	0.9506	2415	777	42.6	7.6
Case 5	0.9718	1977	641.2	27.7	6.1

The results for the high EV uptake show that when all upgrades were considered (Case 4), the only constraint not satisfied was the loading of the cable emanating from the LV busbar. The power generated by the micro-generators (Case 5) was not adequate to reduce the current draw requirement within the sustained rating of the cable. Further cable upgrade from the 300mm^2 cable was not considered because this is the widest cross-sectional area used in LV circuits as reported in [220]-[223].

4.5 PROBABILISTIC STUDY

A probabilistic algorithm was developed to include uncertainties that are anticipated to influence the impact of EV battery charging on the LV operating parameters and equipment. The uncertainties considered are categorised into: (i) EV related parameters, (ii) residential load related parameters and (iii) DG related parameters.

4.5.1 Assumptions

4.5.1.1 EV Related Parameters

The uncertainties related to the EV connection in distribution networks, such as the plug-in time, the location and the charging duration were considered. The electricity use of UK domestic customers at present, is in majority unrestricted (flat price). It is reported in [227] that time of use tariffs were used by 16% of the UK customers in 2007 with Economy 7 being the most widespread. It was assumed that the EV owners will be able to choose between two charging modes.

(i) Uncontrolled or Dumb Charging, where no form of control is applied. The connection of EVs with Economy 7 tariff was assumed to occur at 12 p.m. with a maximum duration of seven hours.

(ii) Smart Charging (SC), where the EV owner will be able to choose the desired battery State of Charge (SoC) and the ending time of the charging session. This mode would allow the utility to control the charging of each battery according to localized constraints and the commuter’s preferences.

Typical UK residential load profiles from [228] show a winter daily peak at 6 p.m. The average daily trip with a car in the UK over the last 30 years has been approximately 20 minutes [204]. The traffic distribution profile from [202] shows a daily peak at 5p.m. This profile was shifted by one hour. It was assumed that the shifted profile corresponds to the commuters’ destination arrival time profile. It was observed that the peak of this profile coincides with the residential peak load (Fig. 4.5). The distribution of the time that EVs are plugged in residences was modelled by a normal distribution. The distribution mean was modelled to be the peak load time and its standard deviation one hour from the peak. This means that the plug-in time would occur within a 6-hour period with a probability of 99.7% (i. e. three standard deviations from the peak load time), and a probability of plugging-in within an hour of the peak load being approximately 68.27%. This means that the density of plug-in time is higher around the peak load time and decreases equally with the divergence from it. This approximation for modelling the EV plug-in time using a normal distribution was the simplest to reflect the home arrival distribution shown in Fig. 4.5.

The duration of EV battery charging depends on the battery capacity, its SoC prior to the connection, and the owner's preferences, such as the time of disconnection and the energy required for charging. The SoC of each EV at the time when each EV owner will plug-in the EV in the residential location and the duration of charging, were modelled as random numbers with a uniform distribution. These variables depend on the use of additional recharging infrastructure from each EV owner, further from the residential charging point considered in this study. The use of a uniform distribution was adopted to exclude higher densities of the SoC and the re-charging time in particular regions, since the presence of additional charging infrastructure was not included in this study. The maximum Depth of Discharge (DoD) was assumed to be 80% [75]. The BEVs were assumed to have a battery capacity of 35kWh and the PHEVs of 9 kWh [4], [76]. The EV battery efficiency was assumed to be 85% and the EV charger efficiency 87%, according to [75], [192].

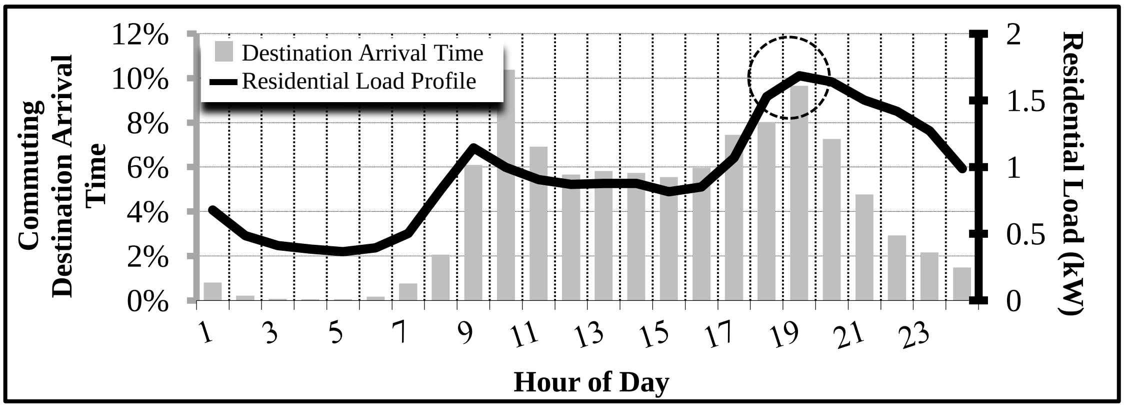


Fig. 4.5 Commuting destination arrival time and typical residential load curves

4.5.1.2 Residential Load Related Parameters

Synthetic profiles were created for each of the 3072 residences (Fig. 4.1). A random daily and a random hourly number were uniformly generated for each profile to create each profile's randomisation factor *(R). R* was calculated by equation (4.1).

$$R = 1 + Sd + Sh \tag{4.1}$$

Where

Sd is the daily and *Sh* is the hourly randomisation factors.

The randomisation factors used, had a maximum of 15% and 20% for each daily and hourly figure [229]. The values of the residential profiles were multiplied by the randomisation factor. In the case study presented in Section 4.5.3, 84% of the customers were assigned an unrestricted load profile and 16% an Economy 7 profile.

4.5.1.3 Distributed Generation Related Parameters

Micro-generation units were considered in the development of the algorithm to enable investigation on the LV studied parameters in networks with DG. They were considered at a domestic scale (i.e. ratings of a few kW) and were modelled as negative loads. Three types of mGen were considered: Wind Turbines (WT), Photovoltaics (PV) and mCHP units. The mCHP technologies considered are Microturbines, Fuel Cells and Stirling Engines, with a Heat to Power Ratio (HPR) of 2.6; 1.4 and 5.0 respectively [230]-[231]. Generation profiles for WT and PV were drawn from [232]. The mCHPs were assumed to follow the heat load, since heat storage was not considered. Typical daily heat load profiles were drawn from [233]. A different generation profile was created for each customer that was assigned an mGen unit, based on equation (4.1). Two mGen penetration levels that were estimated by a colleague PhD student and reported in [234] were used for the year 2030 (Table 4.5).

Table 4.5 mGen penetration estimates for the year 2030 per 384 customers [234]

Component	Unit Power (kW)	Penetration (Units)	
		Low	High
Wind Turbines	2.5	4	11
Photovoltaics	1.5	2	4
Fuel Cell (Natural Gas)	3	3	11
Micro-turbine (Biogas)	3	2	4
Stirling Engine (Wood Pellets)	1.2	13	38
Total Number (Percentage)	-	24 (6.25%)	68(17.7%)

4.5.1.4 Operational States of the Studied Constraints

For a clear interpretation of the sequential load flow outputs, the results are classified into operational states: Normal, Alert and Emergency. The assumed limits for steady state voltage, distribution transformer and the 185mm^2 cable loadings of the UK LV generic distribution network are shown in Table 4.6. The 185mm^2 cable was assumed to be able to sustain up to 145% of its nominal rating for up to four hours. According to [223], when this limit or duration is exceeded, protective devices should operate.

Table 4.6 Assumed state boundaries for LV studied parameters

Parameter	Nominal Rating	State Range (p.u.)		
		Normal	Alert	Emergency
Transformer (summer)	500 kVA	0-1	1-1.2	More than 1.2
Transformer (winter)	500 kVA	0-1.2	1.2-1.4	More than 1.4
185 mm^2 Cable	347A	0-1	1-1.45	More than 1.45
Voltage	400V	0.95-1.09	0.94-0.95, 1.09-1	Less than 0.94, More than 1.1

4.5.2 Description of Probabilistic Algorithm for the Evaluation of EV Impacts on Distribution Networks

The developed algorithm uses a Monte Carlo (MC) procedure (Fig. 4.6). Different sets of input data are obtained from random number generators. Sequential power flows run for two-day duration and the procedure terminates when convergence criteria are satisfied [235]. The samples that are acquired by the MC procedure form the probability densities of the output results. The convergence criterion was the standard error of each node's voltage magnitude for every time-step of the simulation. The MC algorithm halted when all individual standard errors fell below the predefined value (0,001%) to ensure accuracy of the results. The standard error is a common criterion used in commercial MC simulation software packages, such as in Crystal Ball software developed by Oracle [236].

A smart charging re-scheduling algorithm was inserted in the power flow execution stage. When the power flow was called, a routine checked the states of the constraints, according to Table 4.6. If emergency states were found, the charging of an EV was re-scheduled. This means that the EV load was displaced to a subsequent time-step, if the customer preferences allowed the displacement. In the case that a voltage violation was found, the priority of rescheduling was on the vulnerable node. If there was no EV registered in this node, an EV from a neighbouring node was rescheduled. In the case that a cable or transformer overload was found, the priority of rescheduling was on the 96 customer area. The power flow was executed again and the rescheduling routine was re-called if another violation or overload was found. The process is repeated until no violation is detected or no other EVs can be rescheduled.

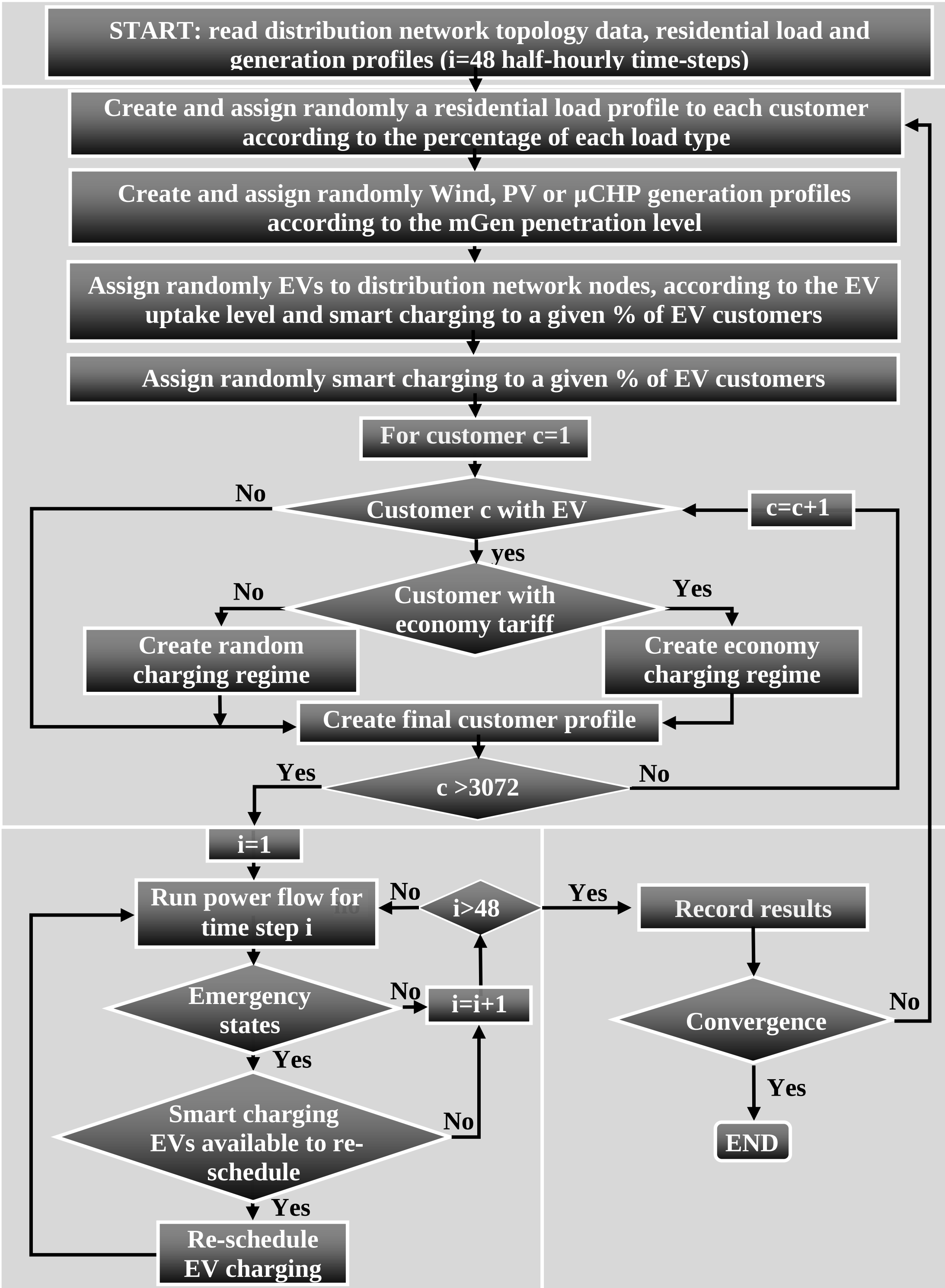


Fig. 4.6 Flow diagram of the probabilistic algorithm

4.5.3 Simulation Results of the Steady State Load Flow Probabilistic Studies

The results of 45 simulations for each season were recorded. The three EV uptake levels of Table 4.1, the two mGen penetration levels of Table 4.4 and five levels of smart charging (from 0 to 100% in 25% steps) were combined. Fig. 4.7-Fig. 4.9 show the probability distributions for steady state voltage, distribution transformer and cable loading of the detailed modelled LV area shown in Fig. 4.1. Each column shows the probability of each state for one scenario. In the horizontal axis, the percentage represents the number of EVs in smart charging mode. In each figure, the upper columns correspond to winter scenario results and the lower columns to summer scenario results. For each EV uptake level, no mGen and the two different mGen penetration levels are considered, and within them, the five smart charging steps are shown. For example, the first column (upper-left) of Fig. 4.7 depicts the case of low EV uptake without smart charging and mGen for winter. For this case, the probability of the most remote node's voltage to be in normal state was found 90%.

4.5.3.1 Voltage

Voltage was found to violate limits only in winter season loading conditions for the medium and high EV uptake cases. Fig. 4.7 shows the distribution of operating states for the voltage of the most remote network node. For summer season loading conditions, the voltage limits would be breached (emergency state) only for the high EV uptake case. The increase in mGen and EV smart charging control, reduce the voltage violations. For the low EV uptake case, 100% application of smart charging among EV owners was found to prevent any voltage violation.

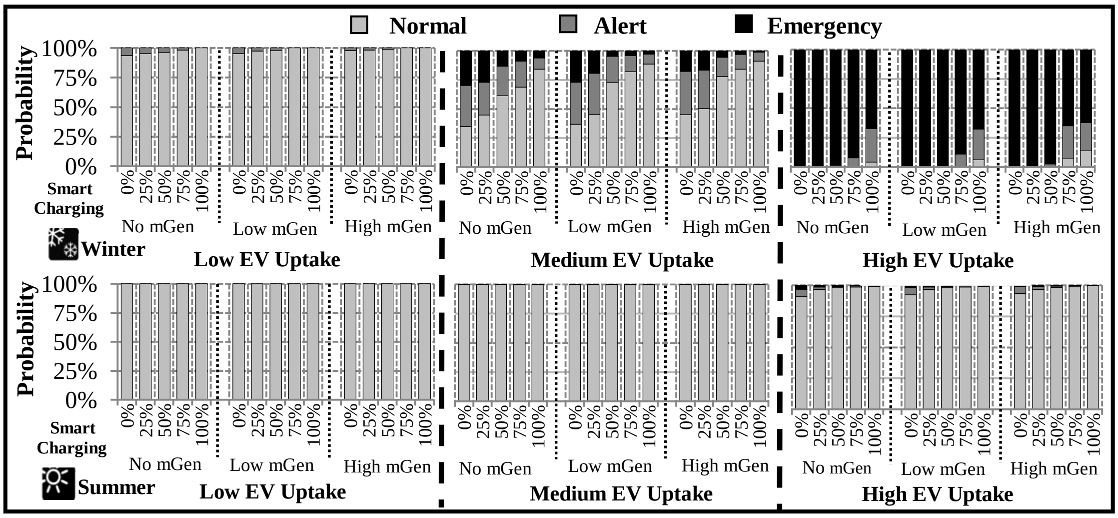


Fig. 4.7 Operational states for steady-state voltage of the most remote node

4.5.3.2 Transformer Loading

The distribution transformer would be overloaded for all cases under winter season system loading. For the summer season loading conditions, the transformer would surpass the normal operational state for the medium and high EV uptake cases. Fig. 4.8 shows the probability of each operational state of the transformer loading.

4.5.3.3 185mm^2 LV Underground Cable

The 185mm^2 cable was found to exceed normal operational state for all EV uptake cases in winter season loading conditions. For the summer season, emergency operational state would occur only for the high EV uptake case. The wide application of smart charging was found to decrease the possibility of alert and emergency states to zero. Fig. 4.9 shows the probability of each operational state of the cable loading.

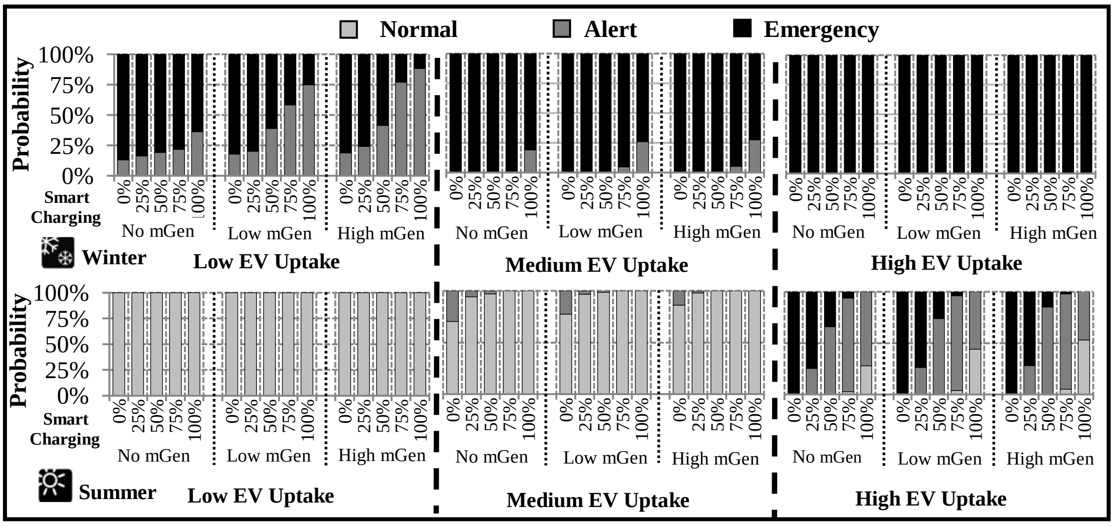


Fig. 4.8 Operational states for distribution transformer

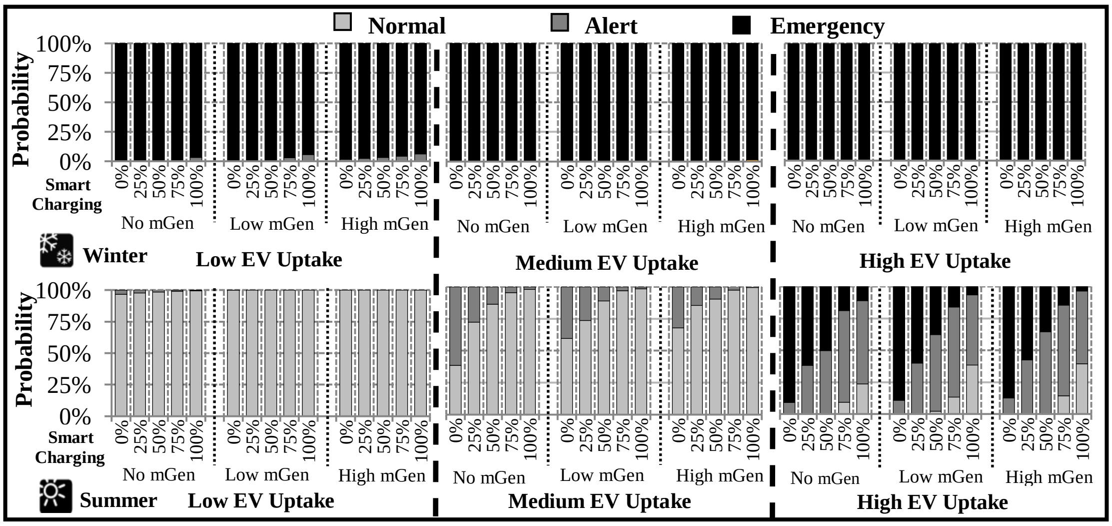


Fig. 4.9 Operational states for 185mm^2 cable

4.5.3.4 Power Line Losses

The electrical losses in the cables of the LV feeder supplying 96 customers were recorded for all simulated cases. Fig. 4.10 shows the daily electrical line losses of the detailed feeder and the fraction of losses/load served (lines corresponding to the secondary vertical axis). It can be seen that a high mGen penetration in 2030 would decrease the losses/load served by approximately 1%. This percentage would further decrease by 1% with a wide deployment of smart charging (i.e. 100% of the EV owners assigned smart charging for the high EV uptake).

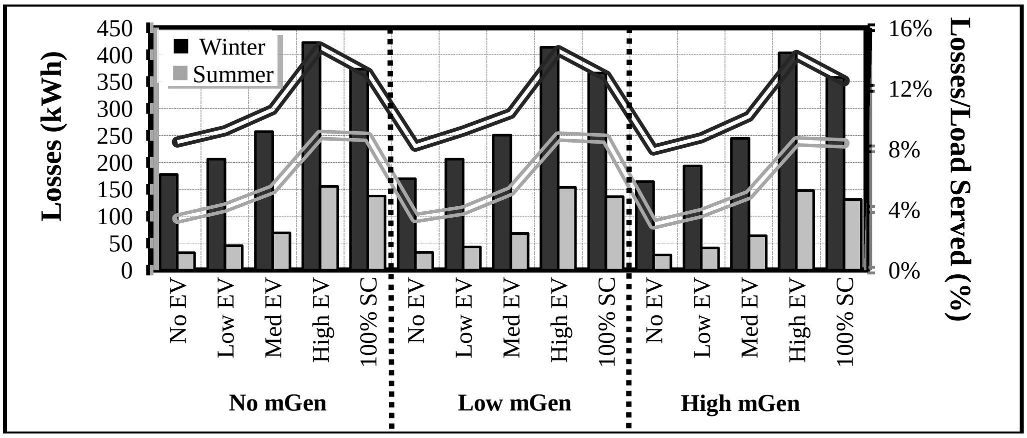


Fig. 4.10 Daily electrical line losses and losses/load served in the LV feeder

4.6 SUMMARY

The effect of electric vehicle battery charging on distribution network's voltage, thermal loadings and electrical line losses was studied. A case study for the year 2030 was built based on EV uptake estimates produced from governmental scenarios. These estimates correspond to 12.5%, 33% and 71% of the residences having an EV and were described as low, medium and high EV uptake levels. Two approaches were used:

1. A deterministic approach used load flow snapshots with a uniform distribution of EV loads across the nodes of a typical UK distribution network. Minimum and maximum network loading conditions were considered. The findings with regards to each technical impact studied for the maximum loading conditions of winter season, were:
   - Voltage was found to violate limits for the medium and high EV uptake levels.

- The cable emanating from the LV busbar supplying 96 households was found to exceed its nominal rating for the medium and high EV uptake levels.
- The distribution transformer was found to be overloaded for all EV uptake levels.
- Electrical line losses in the LV cables were found to increase by 6% for the high EV uptake level, compared to the case without EVs.

A distribution network reinforcement approach was investigated. It was found that a low EV uptake level (see Table 4.4) may be safely integrated with regards to network constraints, by upgrading underground cables and distribution transformers. This solution was found not to be enough for medium and high EV uptake levels. Micro-generators installation will overcome all the constraints for the medium EV uptake level. For the high EV uptake level the transformer loading and the voltage limits were not violated applying both the network reinforcements and the micro-generation installation.

2. A probabilistic approach was employed to tackle behavioural uncertainties of EV owners, residential customers and micro-generation power outputs, types and installation locations. The findings with regards to each technical impact studied for the maximum loading conditions that denotes winter season, were:
   - Voltage was found to violate limits for the medium and high EV uptake levels. The probability of voltage limits violation for the low EV uptake level and the most remote network node, was found to be 4%.
   - The cable emanating from the LV busbar supplying 96 households was found to exceed its nominal rating for all EV uptake levels.
   - The distribution transformer was found to be overloaded for all EV uptake levels. The probability of normal operation was found to be less than 5%.
   - Electrical line losses in the LV cables were found to increase to 14% for the high EV uptake level.

The disparity between the two approaches is due to the uncertainties considered in the probabilistic approach. The non-uniform distribution of EV load among network nodes and the temporal uncertainties of load variations, showed increased currents flowing through the 185mm^2 cable, incrementing the probability of cable overload and electrical losses.

The effect of micro-generation penetration and a controlled regime for EV battery charging were investigated. Two micro-generation penetration levels were used for the 2030 case study, 6.25% and 18%. The smart charging regime was varied between 0-100% in steps of 25%. The results showed that the high penetration level of micro-generation sources and smart control of EV battery charging (100% of EV owners) would eliminate the probability of voltage violations for the low EV uptake. The transformer overload probability would be reduced to 5% from 85%.

From the deterministic and the probabilistic analyses conducted in this chapter, it can be concluded that in order to operate distribution networks with a high EV uptake equivalent to approximately 71% within their technical limits (loading capacity), a combination of reinforcements, installation of micro-generator sources and control of EV battery charging is required.

CHAPTER 5

COORDINATION OF ELECTRIC VEHICLE BATTERY CHARGING WITH A MULTI-AGENT SYSTEM

5.1 INTRODUCTION

Hierarchical structures of agents have been suggested for the aggregation and control of distributed energy resources within multiple Micro-grids [237] and Virtual Power Plants (VPPs) [238]. In [239]-[240] the inclusion of EVs in such hierarchical structures was proposed. In this research the distribution of the hierarchical agents followed the hierarchy of the voltage levels of power distributions networks with:

- A Regional Aggregator agent located at the primary substation level (HV/MV).
- Local Aggregator agents located at secondary substations (MV/LV).
- Electric Vehicle agents located in the EVs or the charging points.

The Regional Aggregator agent manages a number of Local Aggregator agents which are responsible for the management of EV agents that in turn manage a single EV.

The benefits of a hierarchical aggregation structure, in contrast to a single centralised aggregator, include:

- Reliability and robustness: In the case of a failure in a Local Aggregator agent, or an EV agent, only part of the control system is affected [241].
- Simplicity and speed: Data and information are processed locally reducing the complexity of computations and providing faster response [241].

- Flexibility: Each Local Aggregator agent may incorporate characteristics of the area and resources it manages and follow different policies or control strategies from another Local Aggregator agent.
- Extensibility: EV agents operating under the management of a Local Aggregator agent can be added, modified or removed without major amendments in the whole system.

A Multi-Agent System (MAS) for the coordination of electric vehicle battery charging was developed. The MAS coordinates the battery charging of electric vehicles based on:

- Distribution network technical constraints.
- EV owner preferences.
- Electricity prices.

5.2 MULTI-AGENT SYSTEM HIERARCHY

The locations of the agents in a power distribution system are shown in Fig. 5.1.

The **Regional Aggregator (RA) agent** is located at the primary substation level (HV/MV). The RA agent manages a number of Local Aggregator (LA) agents. It aggregates their EV load demand portfolio and communicates with the DSO agent, to ensure that the EV load demand portfolio will not affect normal power system network operating conditions.

The **Local Aggregator (LA) agent** is located at the secondary substation level (MV/LV). It manages the battery charging of EVs that are dispersed in a LV area via their EV agents.

The **EV agent** is located in the electric vehicle and represents the EV owner. It manages the battery charging of a single EV.

The **DSO agent** is located at the primary substation level (HV/MV). It is responsible for the technical operation of the distribution network.

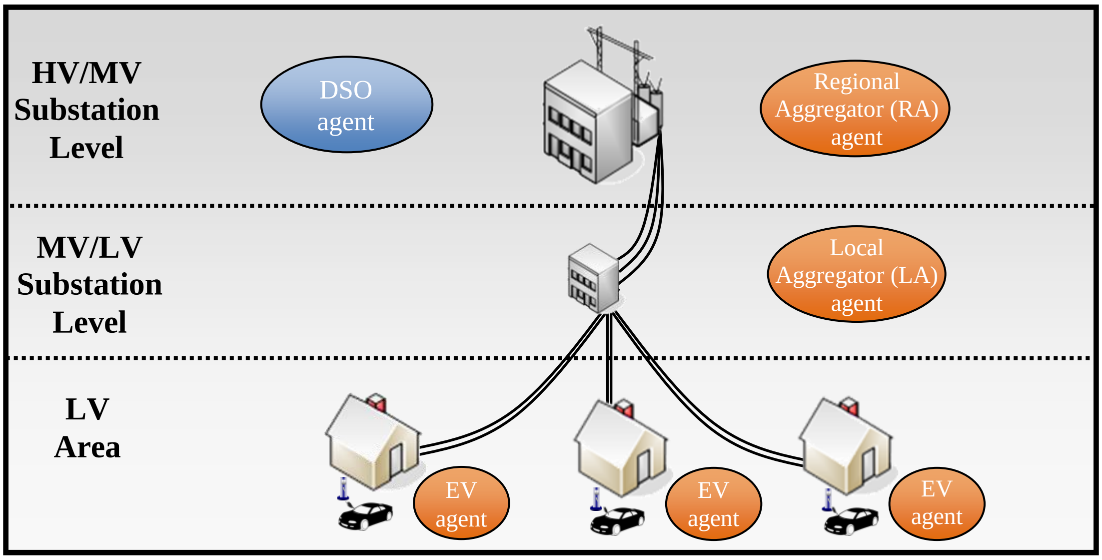


Fig. 5.1 Location of agents in a power distribution system

5.3 Assumptions Used in the Development of the Agent-Based Control System

5.3.1 Real-time Operation with Spot Market Electricity Prices

The MAS satisfies the load demand of the EVs within distribution network limits in the most economic way. In the Directive 2006/32/EC on energy end-use efficiency and energy service of the European Parliament and of the Council [242], it is reported that real-time electricity prices should be offered to customers. A spot price for each hour of a day is sent to each EV agent and is used for the coordination of EV battery charging.

5.3.2 Network Limits Matrix

The distribution network capacity limits are assumed to be defined by the DSO. This concept was proposed in [243]. A matrix with the capacity limits of each LV feeder for each hour of a day is produced by the DSO agent. It is named *network limits matrix* and is made available by the DSO agent to the RA agent. The RA agent sends the network limits for each LV area to each LA agent that in turn uses them to choose the schedules for EV battery charging within technical limits.

The following constraints are considered:

- Distribution transformer loading limits.
- LV cable loading limits.
- Steady state voltage limits.

5.3.3 Network Monitoring System

A network monitoring system is assumed to be in place and provide the DSO agent with real-time measurements for load forecasting, production of the network limits matrix and initiation of corrective actions in the case of emergency. In this MAS, the corrective actions considered are curtailments of EV battery charging.

5.3.4 EV Battery Model

A lithium-ion battery charging characteristic is modelled in the EV agent. The battery charging characteristic comes from a battery manufacturer that supplies batteries to EV makers [244]. The derivation of the battery charging characteristic parameters and its modelling in the EV agent are provided in Appendix C.

5.4 MULTI-AGENT SYSTEM OPERATION

In each hour there is a planning period and an operational period. During the planning period, the set-points of the EVs for the next operational period are decided as shown in Fig. 5.2.

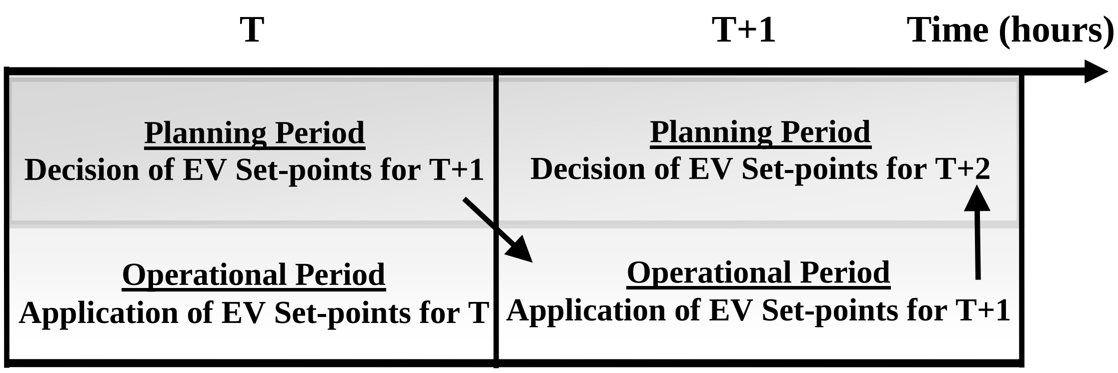


Fig. 5.2 Planning and operational periods of the MAS

The MAS operation includes two modes; normal and emergency operation.

During normal operation, the distribution network is operated within its technical limits. The RA agent, the LA agents and the EV agents communicate during each planning period to decide the EV set-points for the next operational period. At the end of each planning period, the DSO agent evaluates the proposed EV demand. The algorithm for the normal operation is shown in Fig. 5.3.

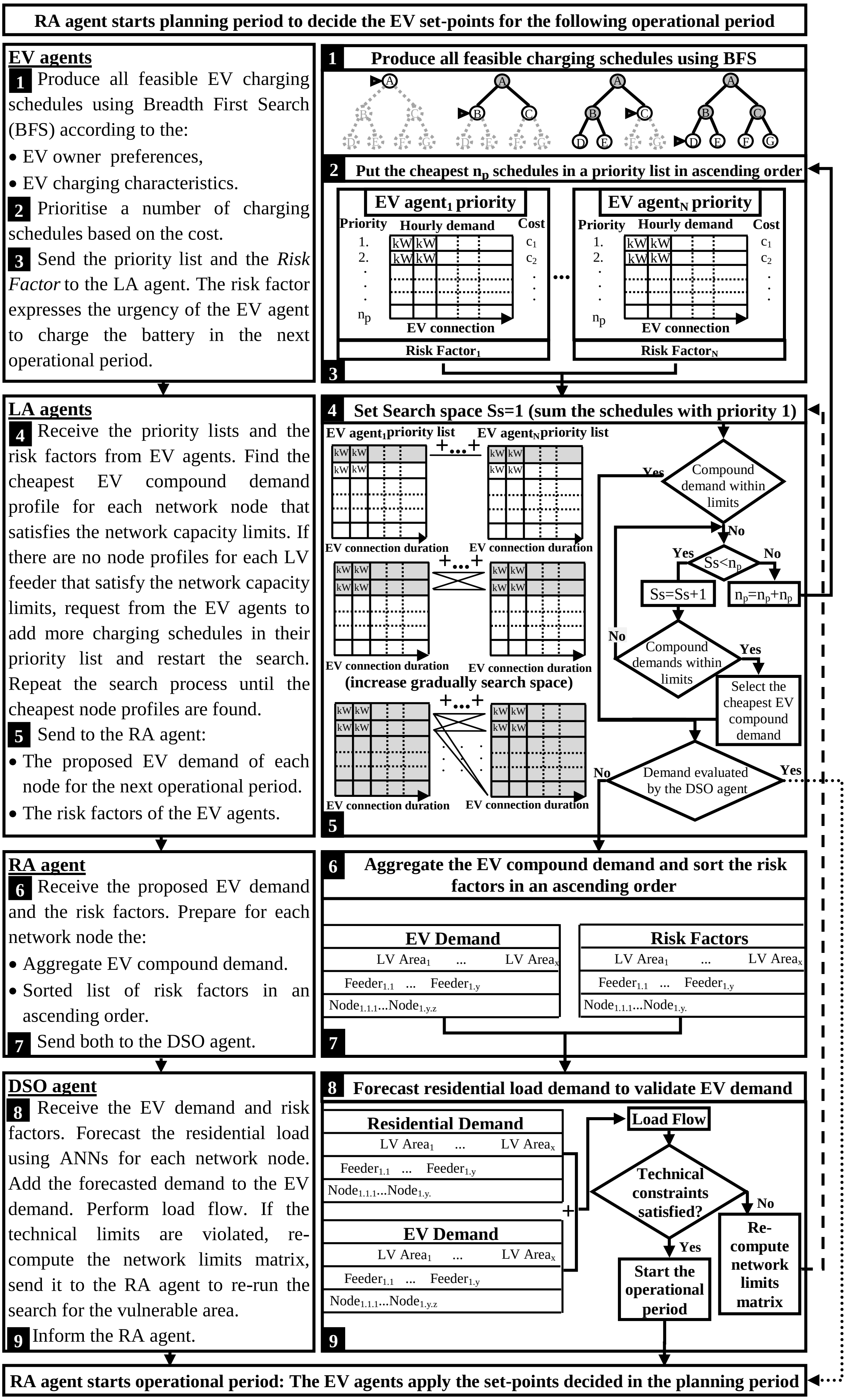


Fig. 5.3 Algorithm of the MAS during normal operation

5.5 Task Decomposition and Algorithms of the Agents During Normal Operation

5.5.1 Electric Vehicle Agent

The EV agent represents the EV owner who has the option to choose:

- The time of EV disconnection.
- The desired SoC of the EV battery at the time of disconnection.
- Whether power injections are allowed from the EV battery to the grid, if the EV is V2G capable.

At the beginning of:

- Every operational period, the EV agent receives a set-point from the LA agent and sends it to the battery inverter of the EV.
- Every planning period, the EV agent receives a message from the LA agent that contains hourly prices for a day and an integer n_p that stands for the number of schedules that the EV agent should form into a priority list. The responding message of the EV agent contains:
  - i) A Risk Factor.
  - ii) A number of n_p charging schedules with the total price of each schedule.

A. <u>Risk Factor</u>

The *Risk Factor* R_f is for the EV owner and is used in the decision making of the DSO agent for EV curtailment in the case of emergency. It is unique for each EV agent at each planning period and expresses the urgency of the EV agent to charge the battery of its EV at the following operational period. It is calculated by equation (5.1).

$$R_f = \frac{SoC_d - SoC_T}{e_B * e_C * P_C * p_c} \tag{5.1}$$

Where

SoC_d is the desired SoC at the time of disconnection in kWh,

SoC_T the estimated SoC of the next operational period in kWh,

e_B is the average battery efficiency,

e_C is the average efficiency of the EV charging point,

P_C the power rating of the charging point in kW, and

p_c is the number of hours that the EV will be connected.

B. EV Agent's Planning Algorithm

The problem of producing a priority list of feasible charging schedules is a finite horizon problem. The horizon is determined by the EV owner. The EV owner will choose the time of EV disconnection once the EV is plugged-in at a charging point.

- The planning horizon comprises a number of finite (fixed) stages $T= \{T_1,...,T_n\}$ that are the number of hours of the EV connection period.
- At each stage, the EV agent has a finite set of feasible actions $A= \{A_1,...,A_k\}$. The range of actions are defined by the EV owner:
  (i) If the EV owner does not allow interruptions of the EV battery charging, the only feasible action is charging,
  (ii) If the EV owner allows interruptions of the EV battery charging, the feasible actions are charging and idle,
  (iii) If the EV is V2G capable and the EV owner allows power injections from the EV to the grid, the feasible actions are charging, idle and discharging.
- An EV charging schedule is the sequence of actions at each stage of the planning horizon and the total price is the sum of hourly costs.

A SoC estimation error and a self-discharge factor are modelled in the EV agent for the calculation of the expected SoC for each time-step of each charging schedule.

- If the Energy exchange is positive (i.e. charge action) or negative (i.e. discharge action), a SoC estimation error is applied.
- If the Energy exchange is 0 (i.e. idle action), a battery self discharge factor is applied.

The modelling assumptions for the SoC estimation and the self-discharge factors are provided in Appendix C.

The EV agent's planning algorithm should produce a priority list of n_p schedules based on the total price in an ascending order. All feasible schedules are calculated by the EV agent and the cheapest n_p are put in the priority list and sent to the LA agent. The remaining feasible schedules are kept in the memory of the EV agent in case the

LA agent requires more schedules in the priority list. The Breadth-First Search (BFS) algorithm is used to obtain all feasible schedules. The BFS algorithm expands firstly the root node of a tree, then all the successors of the root, and then their successors (Fig. 5.4) [121].

A pruning step is added to the breadth-first algorithm. This means that sub-trees that are not going to contain feasible schedules are not further expanded. A schedule is feasible when it satisfies a number of constraints. These constraints are evaluated per stage of the tree expansion. An example and evaluation of the algorithm's performance is given in Appendix D.

C. Constraints in EV Agent's Planning Algorithm

The set of constraints inserted in the pruning step of the BFS algorithm differ according to the preferences of the EV owner.

1) If the EV owner does not allow power injections from the EV battery back to the grid, the constraints are:

i) $20\%*C_B \leq SoC_t$

ii) $SoC_t \leq C_B$

iii) $SoC_t \leq SoC_d$

iv) $SoC_d - tol \leq SoC_{end} \leq SoC_d$

Where:

SoC_t is the estimated SoC at every time-step t of the connection period in kWh,

C_B is the nominal battery capacity in kWh,

SoC_d *is* the desired SoC at the end of the connection period in kWh,

tol is a tolerance factor in kWh,

SoC_{end} *is* the SoC of each schedule produced by the algorithm at the end of the connection period in kWh,

t is each time-step of the connection period.

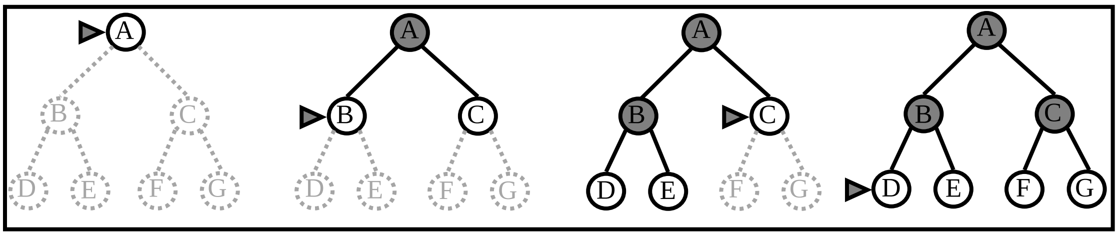


Fig. 5.4 Breadth-first search on simple binary tree. At each stage, the node to be expanded next is indicated by a marker [121]

The schedules that satisfy the constraints are sorted based on the total price in an ascending order. The tolerance variable *tol* is used in the case that the number of schedules produced by the EV agent are less than the number n_p requested by the LA agent.

- In the first run of the algorithm at the beginning of each planning period, the tolerance is set to zero.
- When all feasible schedules have been defined, the algorithm checks whether the number of feasible schedules, are at least equal to the number n_p of schedules requested by the LA agent.
- If the number of schedules is less than the requested, the tolerance is increased by $[SoC_d – SoC_t\ ]$,where *SoCt* is the estimated SoC at the beginning of the following operational period, and the algorithm re-runs. The schedules that do not satisfy the desired SoC_d constraint are sorted according to the SoC_{end} in a descending order and put in the EV agent's priority list after the schedules that satisfy the desired SoC_d constraint.

2) If the EV is V2G capable and the EV owner allows power injections from the EV to the grid, the constraints are:

i) $20\%*C_B \leq SoCt$

ii) $SoC_t \leq C_B$

iii) $SoC_d – tol \leq SoC_{end} \leq SoC_d$

The EV agent may buy additional energy during hours when electricity is cheap and sell it at a later time at higher prices. In order to avoid expansion of sub-trees where profit is not foreseen, the rule shown in equation (5.2) was added to perform consistency checking [121]. "*A heuristic h(n) is consistent if, for every node **n** and every successor **n'** of **n** generated by any action **a**, the estimated cost **c** of reaching the* *goal from **n** is no greater than the step cost of getting to **n'** plus the estimated cost of reaching the goal from **n**'*" [122]. This means that the EV agent allows the buying of additional energy ($SoC_d \leq SoC_t \leq C_B$) if it only foresees that it may sell it later at a higher price and overall has profit and conversely.

$$h(n) \leq c\,(n, a, n') + h(n') \tag{5.2}$$

A battery utilisation cost factor is used. This factor is expressed in £/kWh and stands for the cost of the battery to provide energy back to the grid. It is calculated by equation (5.3). This concept comes from [245].

$$c_{BU} = c_B * \left[\frac{(1+d)^l * d}{(1+d)^l - 1} \right] / (L_c * C_B * e_B) \tag{5.3}$$

Where:

c_{BU} is the battery utilisation cost in £/kWh,

c_B is the capital cost of the battery in £,

d is an annual interest rate of the battery cost,

l_y the lifetime of the battery in years,

L_c is the lifetime of the battery in cycles,

C_B is the battery capacity in kWh and

e_B is the average battery efficiency.

The lifetime of the battery l_y is calculated by equation (5.4).

$$l_y = 365 * L_c / a_{cd} \tag{5.4}$$

Where:

a_{cd} is the average charge/discharge cycles of the EV battery per day.

A sensitivity analysis of the battery utilisation cost is provided in Appendix E and an example of JADE implementation is provided in Appendix F.

5.5.2 Local Aggregator Agent

The LA agent is located at the MV/LV substation level and manages the EV agents of a LV area. At the beginning of every operational period, the LA agent sends the decided set-points to the EV agents. At the beginning of each planning period, the LA agent receives from the RA agent:

- The network limits for each feeder of the LV area it manages.
- The hourly electricity price schedule for a day.

The LA agent sends a message to the EV agents requesting their schedule priority lists, the total price of each schedule in the priority list and their risk factor. When all responses are received, the LA agent searches for the combination of schedules for each node of each LV feeder that satisfies the network loading limits and minimises the total cost. An exhaustive search routine is used for each node of each LV feeder to find the cheapest compound profile. An example is shown in Fig. 5.5.

- The LA agent adds the first schedules of all EV agents that are located in EVs connected to a network node. From the combinations of schedules that satisfy the network limits, the combination with the lowest sum of costs is the solution.
- If no combinations that satisfy the network limits are found, then the combinations of all first and second schedules are evaluated. This process is repeated until a solution is found or the limit n_p is reached.
- If the limit n_p is reached and no solution has been found, the LA agent requests more schedules from the EV agents and the search routine re-runs with an increased search space.

The LA agent multiplies the LV feeder limits from the network limits matrix by a node factor N_f, which is the number of EVs connected to the network node divided by the number of EVs in the feeder, to create network node limits. The exhaustive search is solved per node starting with the node with the highest average of risk factors and moves on with the remaining nodes prioritizing them according to the average of risk factors in a descending order. When the solution for each node is found, each LA agent sends to the RA agent the risk factor of each EV agent for each node and the aggregated EV load demand per node for the following operational period.

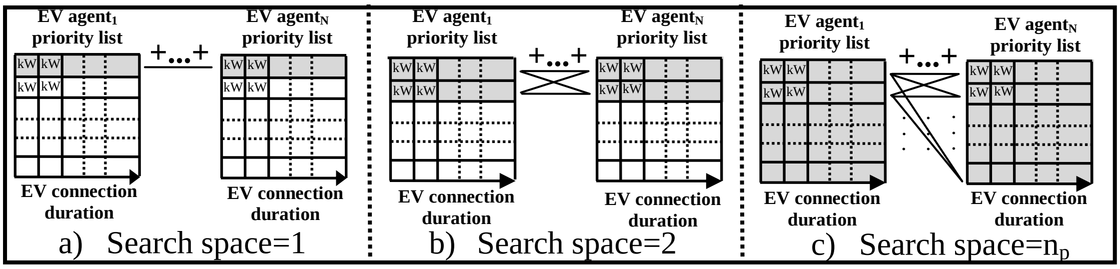


Fig. 5.5 Example of exhaustive search with gradual increase of search space

5.5.3 Regional Aggregator Agent

The RA agent manages the LA agents of a MV network and is located at the HV/MV substation level. At the beginning of every operational period the RA agent sends a message to the LA agents to inform them that the operational period has started.

When it receives all responses from the LA agents that the EV agents have applied their set-points, it sends a message to the LA agents to start the planning period. The LA agents reply with:

- The list of risk factors of the EVs connected to each node of their area.
- The proposed EV load demand per node of the LV area they manage for the following operational period.

The RA agent sends this information to the DSO agent and requests technical validation for the following operational period.

- If the DSO agent validates this demand, the RA agent informs the LA agents that their proposal has been accepted.
- If the RA agent's proposal is not validated, the DSO agent updates the network limits and informs the RA agent. The updated network limits are passed to the LA agents that re-evaluate the schedules of the EV agents.

5.5.4 DSO Agent

The DSO agent represents the DSO and is located at the HV/MV substation level. The DSO agent is responsible for the power delivery in the distribution network within technical constraints. The DSO agent has the following resources:

- The topology of the downstream distribution network.
- The historical load demand of each node of the network.
- The actual demand of each node in real time.
- The risk factor of each EV agent for each distribution network node.

The DSO agent produces the network limits matrix. The network limits matrix is produced via the algorithm shown in Fig. 5.6. This algorithm provides the capacity available for EV battery charging in a LV feeder. This is done by increasing gradually the load in each LV network node, starting from the most remote node, until a technical constraint is violated. In Fig. 5.6:

- The variable *L* is the load step increase.
- The variable *T* denotes 24 hourly time-steps.
- The variable L_c is a counter that is used to record the added load.

At the end of each planning period, the DSO agent:

- Receives from the RA agent the proposed EV demand and the risk factors of the EV agents for the following operational period.
- Forecasts the residential load demand of each node of the distribution network for the next operational period using neural networks.
- Adds the forecasted residential load demand to the proposed EV demand.
- Runs a load flow and checks whether the proposed EV demand will affect normal operating conditions in the next operational period.

In the case of technical invalidation, the DSO agent updates the network limits matrix and sends them to the RA agent. The network limits are then assumed final.

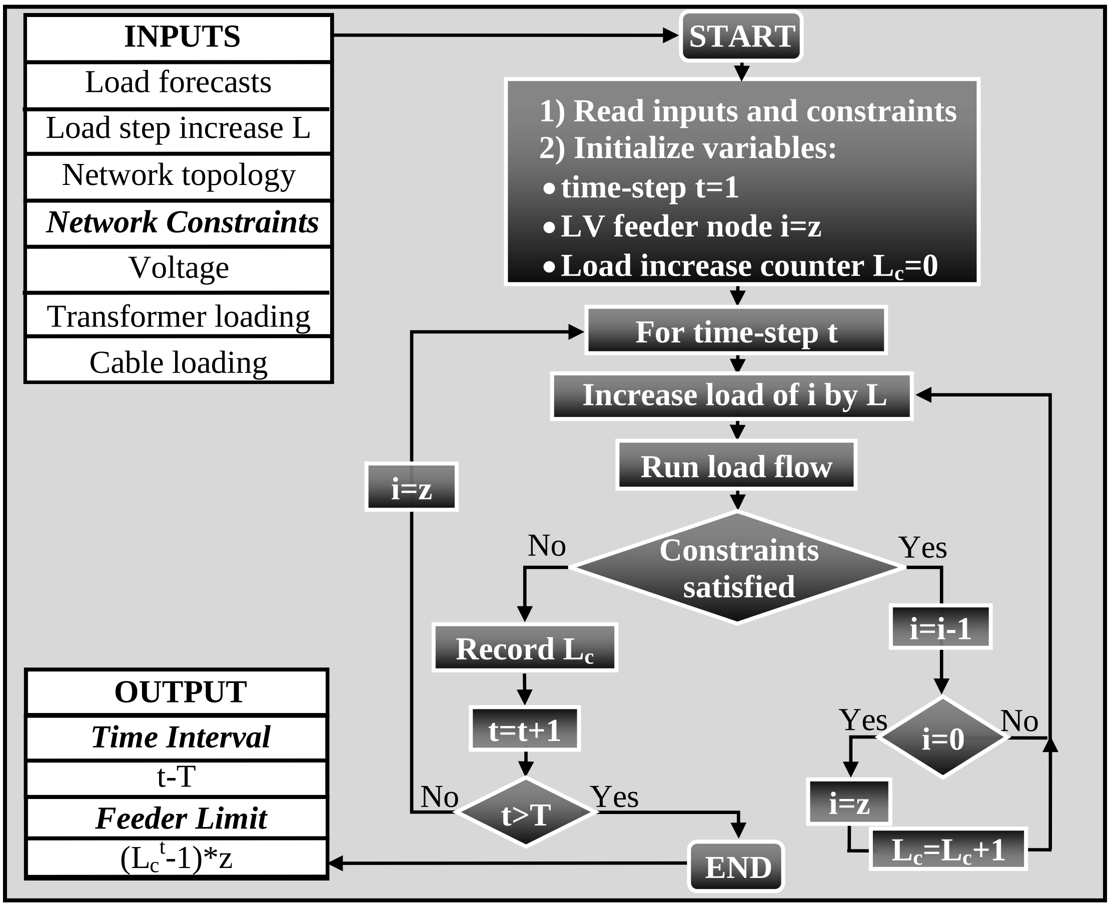


Fig. 5.6 Network limits matrix algorithm

5.6 Task Decomposition and Algorithms of the Agents During Emergency Operation

If an emergency situation occurs (i.e. voltage violates limits or transformers or cables are overloaded), the MAS reacts autonomously to restore normal operating conditions. The algorithm for the emergency operation is shown in Fig. 5.7.

5.6.1 DSO Agent

The DSO agent that monitors the network nodes, detects the limit breach and:

- Curtails gradually the EVs starting with those with lowest individual risk factor of the affected network node.
- Curtails EVs from neighbouring nodes if there are no EVs connected in the node that the violation was found. The neighbouring node is chosen based on the lowest risk factor of the EV agents.
- Curtails EVs randomly if the risk factors of EV agents are equal.

The curtailing procedure stops only when normal operation is restored.

5.6.2 Regional Aggregator Agent

After the emergency event (when normal operating conditions are restored), the RA agent is directly notified by the DSO agent and initiates an emergency planning period.

5.6.3 Local Aggregator Agent

The LA agent that manages the EV agents in the area of emergency receives a message from the RA agent after normal operating conditions have been restored, to start an emergency planning period.

5.6.4 Electric Vehicle Agent

During the emergency, the EV agent receives a curtailment request from the DSO agent and sends a set-point of zero current to the battery inverter of the EV. After normal operating conditions are restored, the EV agent produces a priority list of charging schedules and sends it to the LA agent together with a risk factor.

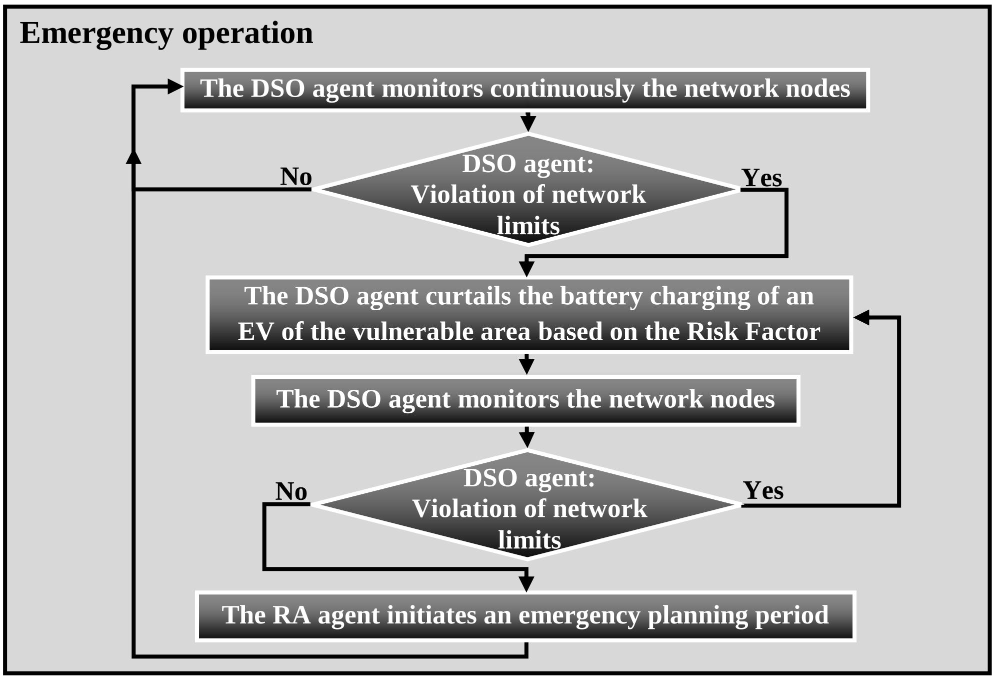


Fig. 5.7 Algorithm of the MAS during emergency operation

5.7 Short Term Load Forecasting with Artificial Neural Networks

The DSO agent requires a load prediction for the domestic loads of each network node. A single value for each node of the distribution network is required as a prediction output. Artificial neural networks are used for short term load forecasting.

5.7.1 Architecture of Artificial Neural Network

Two options were considered to decide the architecture of the ANNs:

- A single ANN that predicts the load per node for all network nodes.
- An ANN for each network node. This option was employed to avoid false predictions for all network nodes in the case of a single ANN fault.

The input data typically used in ANNs for short term load forecasting are historical load and weather (temperature and in some cases humidity) data, according to [246]. Due to the lack of weather data, the developed ANN uses only historical load data.

A Multi-Layer Perceptron (MLP) is implemented for each network node. Each MLP uses load data from two previous days and the day that prediction is required. The two previous days are assumed to be the day before the day that prediction is required, and the same day of the prediction of previous week. The training data of each MLP are the half-hourly node load values of the two previous days and the testing data the equivalent values of the current day. The training data are normalised to a maximum value of 1 because it is required by the activation function used.

Each MLP has 48 neurons in the input layer, 97 neurons in the hidden layer and one neuron in the output layer. The number of neurons in the hidden layer was decided after trial and error. The training of each network is done using Encog's iPROP^{+} [180] algorithm (provided in Appendix A) and stops when the Mean Square Error (MSE) falls below 0.1%. This stopping threshold was decided after tests. The characteristics of the neural network are shown in Table 5.1.

$$MSE = \frac{1}{i_n} \sum_{i=1}^{i_n} (\hat{y}_n - y_n)^2 \tag{5.5}$$

Where

y_n is the actual output,

$\hat{y}_n$ is the desired output,

i_n is the number of iterations.

Table 5.1 Characteristics of neural network for load forecasting

Network Type	**Activation Function**	**Number of Neurons**			**Training Algorithm**	**Early Stopping Criterion**
		Input Layer	*Hidden Layer*	*Output Layer*		
MLP	Tanh	48	97	1	iPROP+	MSE<0.1%

5.7.2 Evaluation of Artificial Neural Network

The accuracy of the ANN was tested. 500 days were simulated. A 24-customer node profile was used. This profile consisted of a combination of unrestricted residential load profiles (84%) and Economy 7 residential load profiles (16%), from [228]. Three profiles were created from this profile for each simulated day. Two of them were used to train the ANN and the third for the testing procedure. One random daily and one random hourly number were uniformly generated for each profile to create each profile's randomisation factor. This factor was calculated by equation (4.1) and the process is explained in Section 4.5.1.2.

The Mean Absolute Percentage Error (MAPE) defined in equations (5.6)-(5.8) was used to evaluate the accuracy of the ANN.

$$MAPE\ (d,h) = \frac{|\ y(d,h) - \hat{y}(d,h)\ |}{\hat{y}(d,h)} \tag{5.6}$$

$$MAPE\ (d) = \frac{1}{24}\sum_{h=1}^{24} MAPE\ (d,h) \tag{5.7}$$

$$\overline{MAPE} = \frac{1}{N_d}\sum_{d=1}^{N_d} MAPE\ (d) \tag{5.8}$$

Where

N_d is the number of simulated days,

d is the day index,

h is the hour index.

The $\overline{\text{MAPE}}$ for all simulated cases was found to be 2.17% and the daily deviation from the total absolute average error 1.13%. The worst and best daily forecasts were recorded and shown in Fig. 5.8 and Fig. 5.9.

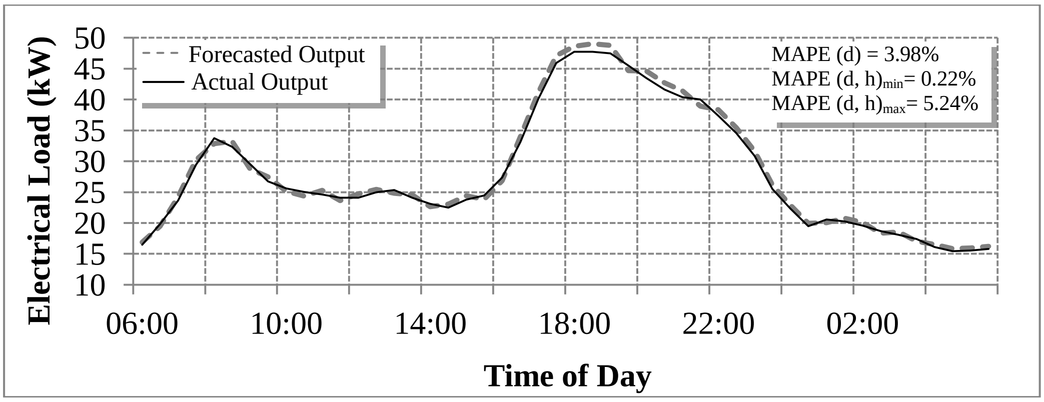


Fig. 5.8 Forecasted and actual load profiles for the case with the worst MAPE (d)

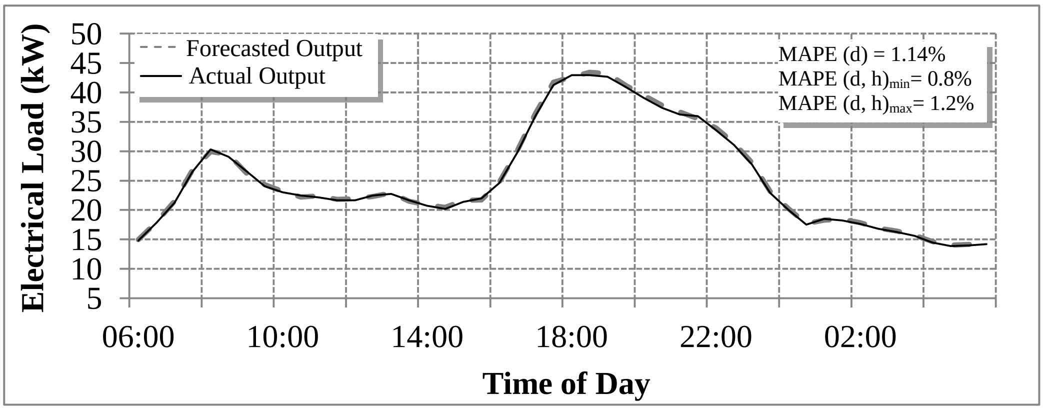


Fig. 5.9 Forecasted and actual load profiles for the case with the best MAPE (d)

5.8 SUMMARY

A multi-agent system for the coordination of EV battery charging in distribution networks was described. The location of the agents in a distribution network was provided.

Four types of agents were described:

- A Regional Aggregator (RA) agent located in the primary substation level.
- A Local Aggregator (LA) agent located in the secondary substation level.
- An Electric Vehicle (EV) agent located in the EV.
- A DSO agent would be located at the primary substation.

The algorithms of each agent were provided. The MAS operates in two modes, normal and emergency. Therefore, two main algorithms were created and described:

- One algorithm for normal operation that is executed continuously when the distribution network is operated within its technical limits.
- One algorithm for emergency operation that is executed when voltage of the LV area violates limits or transformers and cables are overloaded.

An Artificial Neural Network (ANN) was developed for short term load forecasting. The ANN is used by the DSO agent to forecast the residential load of each node of the distribution network.

CHAPTER 6

EXPERIMENTAL EVALUATION OF THE MULTI-AGENT SYSTEM

6.1 INTRODUCTION

The operation of the MAS proposed in Chapter 5 to coordinate EV battery charging was tested in the DER laboratory of the research institute Tecnalia in Spain. In this chapter the outcomes of the testing are provided. A test feeder was created to demonstrate in real-time the online operation of the MAS under normal and emergency operating conditions of the electrical network and three different policies of the MAS.

The laboratory setup and a software agent created to monitor and control the equipment of the physical devices were accomplished with the help of Tecnalia personnel. This work was done under the framework of the EU FP7 project Distributed Energy Resources Research Infrastructures in collaboration with a colleague PhD student. The deliverable report document can be found in [247].

6.2 EXPERIMENTAL SETUP

6.2.1 Testing Requirements

The MAS operation was evaluated using the detailed feeder of the LV part of the UK generic distribution network presented in Chapter 4. The detailed feeder is referred to as residential feeder in Fig. 6.1 and was assumed to comprise of 96 domestic loads and 32 electric vehicles, uniformly distributed throughout the network nodes and managed under a Local Aggregator agent. The remaining 288 domestic loads and 96 EV agents of the LV area were simplified as lumped loads. The EV uptake level is the medium uptake level of 33% used in Chapter 4 of this thesis.

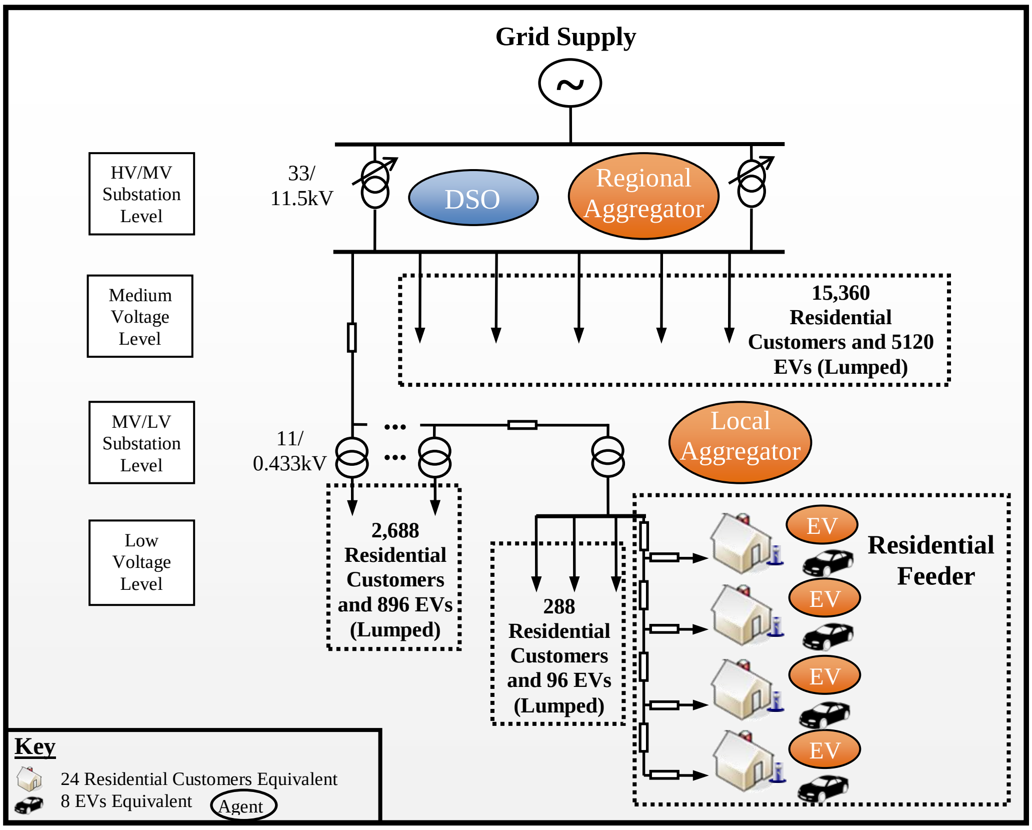


Fig. 6.1 UK generic network and the residential feeder simulated in Tecnalia's laboratory

The design aim for the laboratory testing was to create an equivalent circuit of the residential feeder. The requirements for this setup and the MAS testing were:

- Resistive controllable loads and/or energy storage devices to emulate the loading behaviour of the LV feeder.
- Cables and links for creating the equivalent circuit.
- Monitoring devices for acquiring measurements from the constructed circuit.
- Data acquisition and communication software for transferring measurement data to the software agents.
- Communication software for monitoring and control of the loading of the equivalent feeder.

The laboratory of Tecnalia research institute was used for the testing of the MAS because it met these requirements and in addition provided the EV-ON platform. The EV-ON platform is a cluster of software and hardware resources that emulates the behaviour of an actual electric vehicle. An EV agent was adapted to it.

6.2.2 Hardware and Software Resources

The laboratory of Tecnalia provides connections to DER equipment via cables emanating from the laboratory switchboard which is connected to the LV distribution network through the laboratory building. The following hardware and software resources of the laboratory were used:

- The EV-ON platform, which comprises of commercial hardware and dedicated software for SoC measurement acquisition and set-point application.
- The Avtron Millennium resistive load bank with a total load of 150kW.
- The Avtron K595 resistive load bank with a total load of 39kW.
- The GaugeTech DMMS300 measurement device.
- The communication software and infrastructure for acquiring measurements from the measurement device and monitoring and controlling the load banks, was provided by Tecnalia. The software used is named Communication Software for Distributed Energy Resources (CSDER) [248].

6.2.2.1 EV-ON Platform

The EV-ON platform was not directly connected to the laboratory switchboard and was not mapped to the CSDER. This means that the SoC acquisition and the set-points application were not performed through CSDER but directly via dedicated software developed by Tecnalia to control the inverter of the EV-ON platform. Fig. 6.2 shows the EV-ON platform.

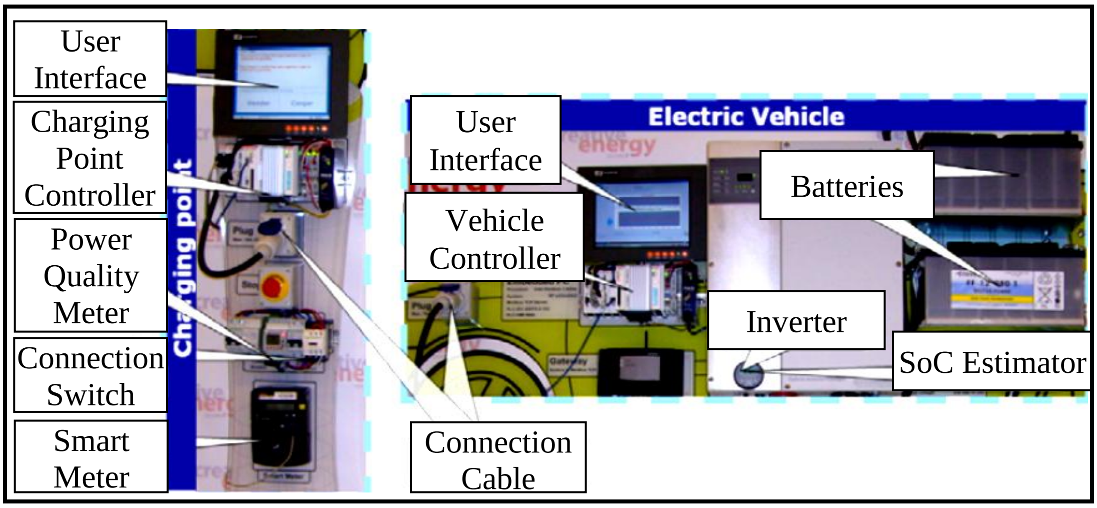


Fig. 6.2 EV-ON platform of Tecnalia [249]

The hardware components that were used from the charging point of the EV-ON platform [250] (see left side of Fig. 6.2) are:

- Charging point controller: Industrial embedded PC (Beckhoff CX 1030) with Microsoft Windows XP embedded operating system.
- Plug: SCAME (Libera series for EVs).
- User interface: Axiomtek panel 6100-O/P 10.4 industrial Thin Film Transistor-Liquid Crystal Display (TFT-LCD) monitor with touch screen.

The hardware components that were used from the electric vehicle of the EV-ON platform [250] (see right side of Fig. 6.2) are:

- Vehicle controller: Industrial embedded PC (Beckhoff CX 1030) with Microsoft Windows XP embedded operating system.
- Inverter: Xantrex XW4024 (230V/50Hz). Hybrid charger/inverter controllable by means of XanBUS proprietary protocol (accessed by the vehicle controller through a gateway to Modbus protocol).
- Batteries: Standard vented lead acid batteries of 2.64 kWh total capacity.
- SoC estimator: Xantrex DC-Link pro.
- User interface: Axiomtek panel 6100-O/P 10.4 industrial TFT-LCD monitor with touch screen.

Dedicated software developed by Tecnalia was adapted to one EV agent to:

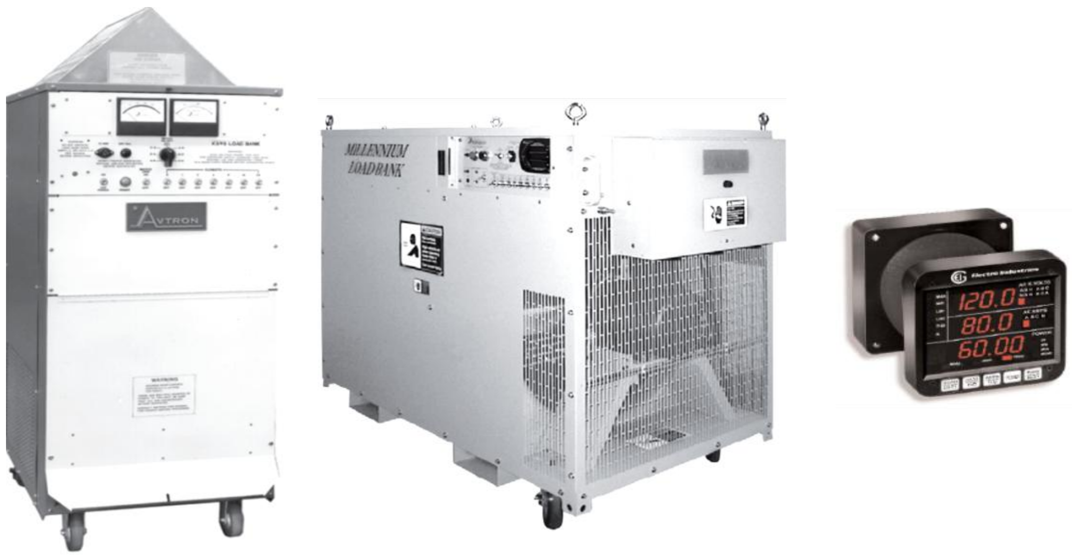
- Retrieve SoC measurements,
- Apply current set-points to the inverter.

6.2.2.3 Resistive Load Banks and Measurement Device

Two resistive load banks with a total load of 189kW were used to emulate the loading of the residential feeder. The load banks were connected to the three phases of the LV busbar of Tecnalia’s laboratory. A measurement device was used to provide active power (P), reactive power (Q) and three phase voltage (V) measurements. This device was installed on the busbar of the lab switchboard and was mapped to the CSDER. The individual load steps of each load bank are provided in Table 6.1 and the pictures of each load bank and the measurement device are shown in Fig. 6.3.

Table 6.1 Individual load steps of each load bank

Load Bank	**Available Load Steps (kW)**						
Avtron K595	0.35	0.75	1.39	2.78	5.56	11.11	16.67
Avtron Millenium	5.0	10.0	10.0	25.0	50.0	50.0	



a) Avtron K595 load bank

b) Avtron Millennium load bank

c) GaugeTech DMMS300 measurement device

Fig. 6.3 The resistive load banks and the measurement device used in Tecnalia's laboratory [251]-[253]

6.2.2.4 Communication Software for Distributed Energy Resources

The CSDER, "*offers the way to translate a range of proprietary communication protocols used by different DER to a form of the IEC 61850 based protocol*" [248]. The CSDER is implemented in JAVA^{TM}, therefore it was readily available for use with the MAS. It was used as a gateway between the software agents and the physical devices of the laboratory. The server hosting the CSDER resources for the monitoring and control of the physical equipment was installed in the laboratory facilities of Tecnalia. Details of the implementation of CSDER can be found in document [248]. The high-level software architecture of CSDER is shown in Fig. 6.4.

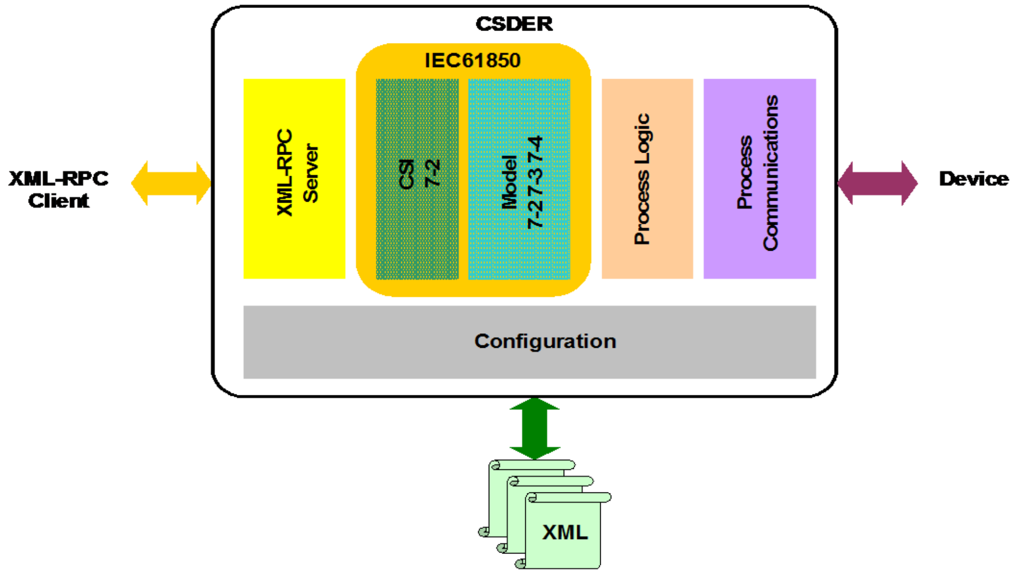


Fig. 6.4 High-level software architecture of CSDER [248]

A software agent was created to monitor and control the load bank's steps in order to vary the loading conditions at each time-step of the experiments. This agent is named Load Banks Controller (LBC) agent. A CSDER client was instantiated at the initiation of each experiment in this agent. Through that client, command signals were sent to CSDER to:

- Monitor the steps of each load bank that were switched on.
- Alter the state of each load bank's load step.

Another CSDER client was instantiated in the DSO agent at the initiation of each experiment. Through that client, the DSO agent was instructed to acquire periodically real power (P), reactive power (Q), and voltage (V) measurements from the measurement device, through the CSDER. The periodical measurement acquisition function was implemented using JADE functionality (i.e. the ready-made class TickerBehaviour provided freely with JADE source code) [161].

6.2.3 Load Banks Controller Agent

The role of the LBC agent was to calculate the load bank steps required to be switched on and off, in order to create the loading conditions of the simulated LV feeder at each time-step of the experiments. The feeder loading at each time-step of the simulation was formed by summing the domestic load values and the EV load values. The domestic load values were input at the beginning of each experiment and the EV load values were the output of the MAS decision making after each planning period.

A scaling factor μ was applied by the LBC agent, since the maximum demand of the feeder in kW was greater than the total load that the load banks provide. This factor was calculated by equation (6.1).

$$\mu = \frac{L_{max}^{sim}}{L_{max}^{lab}} = \frac{243.59\ (kW)}{188.61\ (kW)} = 1.29 \tag{6.1}$$

Where

L_{max}^{sim} is the maximum load demand in kW of the feeder used in the case studies (i.e. the maximum sum of domestic loads and EV load demand),

L_{max}^{lab} is the maximum load of the load banks in kW.

During normal operation, the steps followed by the LBC agent were:

1. Read from a file the domestic load demand prior to the initiation of every operational period,
2. Acquire the EV load demand from the LA agent after the set-points validation from the DSO agent,
3. Add the domestic and EV load demands and apply the scaling factor,
4. Calculate the combination of load bank steps required to be switched on from each load bank to achieve the desired feeder loading,
5. Send commands to each load bank through CSDER for switching.

During emergency operation, the Load Banks Controller agent was receiving an instruction from the DSO agent to curtail the equivalent load of an EV. The steps followed by the Load Banks Controller agent during emergency operation were:

1. Retrieve the total demand value of the LV feeder for the current time-step,
2. Subtract the demand of the EV that is to be curtailed from the total feeder's demand,
3. Apply the scaling factor,
6. Calculate the combination of load bank steps required to be switched on from each load bank to achieve the desired feeder loading,
4. Send commands to each load bank through CSDER for switching.

6.2.4 Test Network Configuration in Tecnalia's Laboratory

Thirty-six (36) agents were executed in total for the tests that took place in Tecnalia's laboratory. All agents were hosted on one JADE platform that was running on one computer. The configuration used to test the operation of the MAS is shown in Fig. 6.5. The following instances were run:

- 32 EV agents, from which one was adapted to the EV-ON platform,
- One LA agent, one RA agent, one DSO agent and the Load Banks Controller agent.

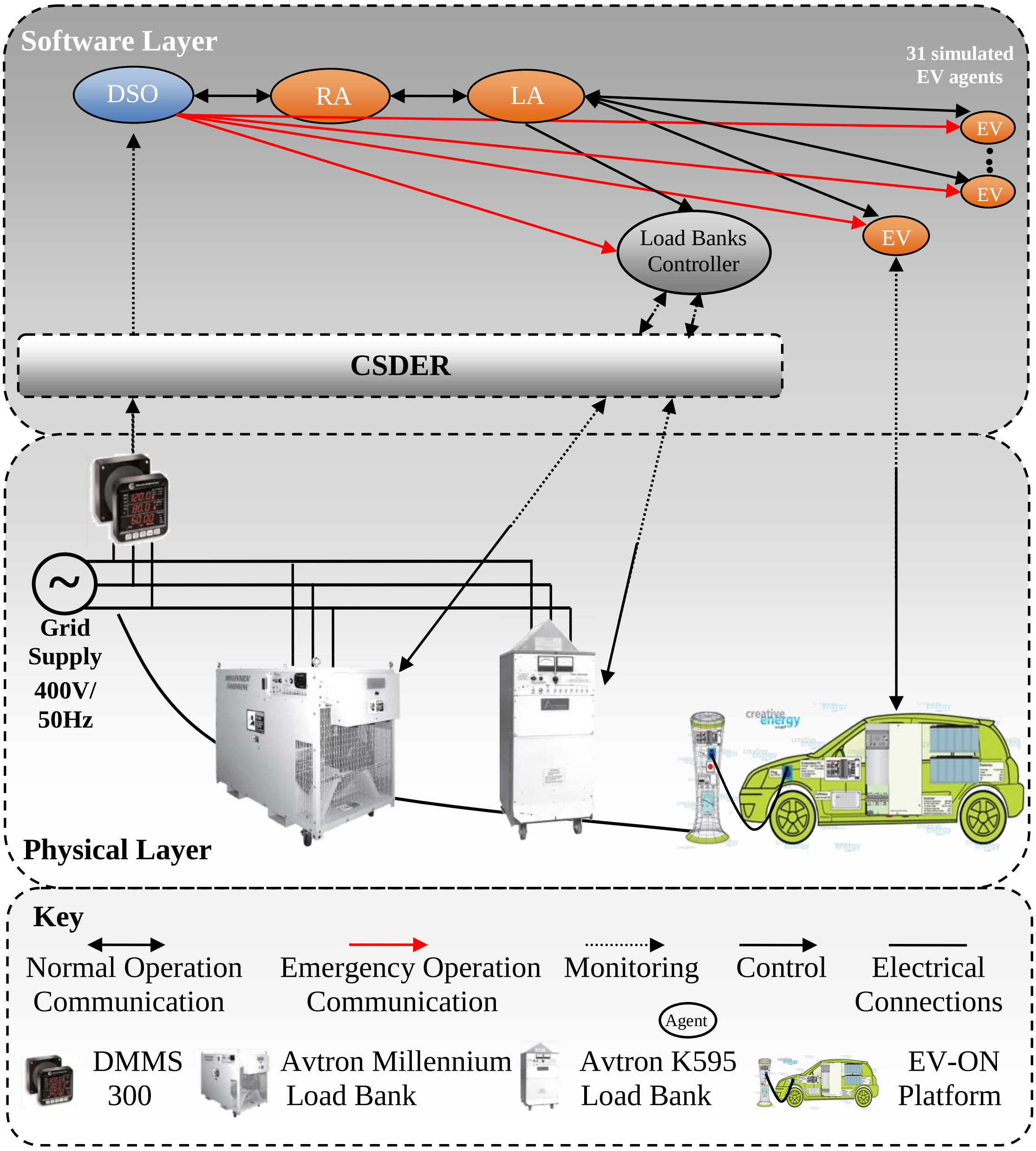


Fig. 6.5 Configuration of test network in Tecnalia's laboratory

6.3 EXPERIMENTAL PROCEDURE

6.3.1 Input Data for Experiments

Domestic load profiles for winter season were drawn from [228]. On average, 16% of the customers were assumed to have an Economy 7 tariff profile and the rest an unrestricted profile. An annual load increase of 1% for the year 2030 was considered from the maximum value of 1.3kW per customer in 2003 [220].

Electricity prices were drawn from [254]. The hourly prices of all winter days for the winter of the year ending 2010, were averaged to create a single daily electricity price profile. The domestic load profile that was used for each of the four 24-customer nodes of the LV feeder and the electricity price profile are shown in Fig. 6.6.

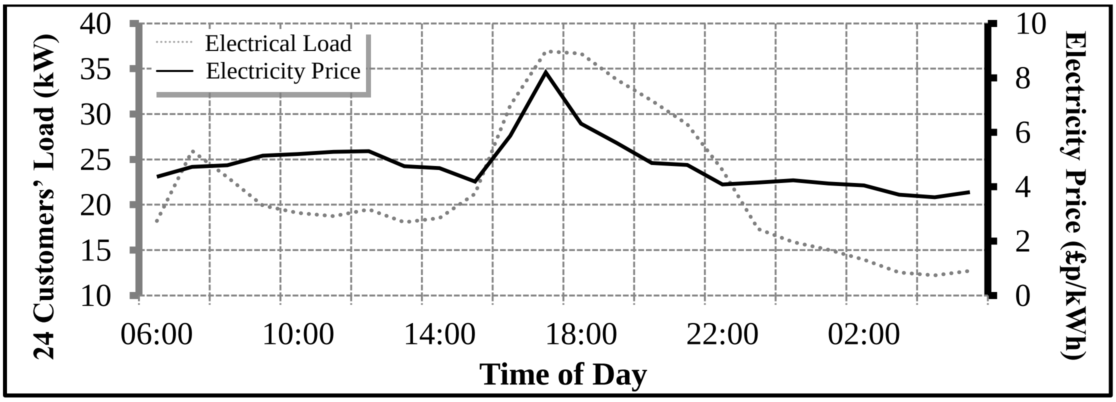


Fig. 6.6 Load profile per 24 customers and electricity prices used in the experiments

6.3.2 Assumptions Used in the Experiments

An equivalent of the residential feeder was created in the laboratory to test the MAS operation. The assumed limits for the residential feeder are summarised in Table 6.2, according to the analysis provided in Chapter 4 (Table 4.5).

The feeder loading limit of 175kVA was assumed, that is 25% of the transformer winter loading limit of 700kVA. The cable impedances of the laboratory connections were neglected. Resistive load banks were used in the laboratory and the equivalent load of the EVs was assumed also purely resistive. The electrical line losses for the

Table 6.2 Assumed limits for the operating parameters of the case study feeder

Voltage lower limit	0.94 (p.u)
Voltage higher limit	1.1 (p.u.)
185mm^2 cable current flow limit	347 (A)
LV feeder's apparent power flow	175 (kVA)

loading of the feeder during winter season with the medium EV uptake were found to be 4.1% (Fig. 4.5). The feeder loading limit was reduced to 167.825kVA to consider this value.

Cable thermal limits were not used in the evaluation of the MAS operation. The cables connecting the load banks to the switchboard's busbar were not equipped with any measurement device mapped to the CSDER. Other monitoring equipment that could provide online measurements to the software agents was not readily in place.

Voltage limits were also not used. The laboratory switchboard where the measurement device was installed was continuously grid connected and feeding additional devices in the laboratory apart from the ones used for the testing of this MAS. Therefore, the voltage was not controllable.

A 33% EV uptake was assumed (medium EV uptake level in Table 4.1). The fraction of BEVs to PHEVs was assumed 1/1. The EVs were uniformly distributed among the network nodes, i.e. four BEVs and four PHEVs per LV segment.

The daily energy requirement for each EV was determined according to [4]. The average annual driving distance in 2030 for a car in the UK was assumed in [4] to be 21,331 km, or 58.5km daily. An efficiency of 0.11kWh/km for 2030 based on [4], gives on average 6.5kWh daily energy requirement approximately. This figure was used in the case studies as the daily energy requirement of EVs.

The initial SoC of EVs prior to the connection was assumed 30%. The battery capacities of BEVs were assumed to be 35kWh and the battery capacities of PHEVs 9kWh with a maximum allowable Depth of Discharge (DoD) of 80% to prolong battery life [75]. The BEVs were assumed to connect at 18:00, half of the PHEVs at 17:00 and the rest at 19:00. The hour commencing 18:00 is the peak load hour for a winter day and in Chapter 4 it was assumed to be the main home arrival time in (Fig. 4.5). The time of disconnection for all EVs was assumed to be the end of the simulated day (i.e. 06:00 the following morning). The EV parameters used in the case study are shown in Table 6.3.

Table 6.3 Assumed EV parameters used in the case studies

BEV battery capacity (kWh)	35	BEV initial State of Charge (%)	30
PHEV battery capacity (kWh)	9	PHEV initial State of Charge (%)	30
EV charging point rating (kW)	2.99	EV energy requirement (kWh)	6.5

6.3.3 Experiments

Five experiments were conducted in total (Table 6.4). In all experiments, the goal was to minimise the cost of charging. There were three purposes for the experiments:

- Three experiments aimed to evaluate the behaviour of the MAS during normal operating conditions, applying different policies/control strategies.
- One experiment aimed to evaluate the operation of the MAS during a load increase foreseen by the DSO agent in the short term.
- One experiment aimed to evaluate the operation of the MAS during an emergency event.

Table 6.4 Description of experiments

Experiment	Conditions	Purpose
Experiment 1	Normal operating conditions.	To evaluate the MAS operation during normal operating conditions aiming to follow the electricity price signals.
Experiment 2	Normal operating conditions, aiming to minimise the EV load demand in a **specific**	To evaluate the MAS operation when the demand reduction would be required in the LV area, during a specific hour.
Experiment 3	Normal operating conditions and allowing EVs to provide power **back to the grid.**	To evaluate the MAS operation when power injections would be required from the specific LV area, during a specific hour.
Experiment 4	Simulating a **technical invalidation** from the DSO agent.	To evaluate the MAS operation during a load increase that would be foreseen to occur in the short-term (the hour before energy delivery) and was not previously forecasted.
Experiment 5	Simulating **emergency** operating conditions.	To evaluate the MAS operation during an unforeseen load increase in real-time. This load increase would create a violation of the feeder limit.

6.3.4 Experimental Parameters

Each experiment had a daily horizon with 24 hourly time-steps. Each time-step was scaled to a 1-minute interval. The time interval was chosen to be small for two reasons:

(i) To minimise the use of the laboratory facilities and energy use.

(ii) To simulate the lithium-ion battery characteristics provided in Appendix C, using the lead-acid batteries of the EV-ON platform.

The simulation of the lithium-ion battery characteristics using the EV-ON's lead acid batteries, was constrained by the available capacity of the batteries.

- The capacity of the batteries used in the EV-ON platform was 2.64kWh and the minimum SoC allowed was 50%, to extend their lifetime.
- The charging and discharging of the batteries was performed in a SoC range between 50%-75% because above 75% SoC, the batteries were entering a constant voltage charge state and the charging current was not fully controllable.

The available controllable capacity of the batteries was approximately 0.66kWh. The time for charging continuously the battery within the controllable range was found to vary between 10-20 minutes for a current set-point of 13A AC, due to voltage fluctuations and errors of the EV-ON's SoC estimator. The modelled battery would require a period between 3-6 hours to acquire 6.5kWh capacity depending on the initial SoC and the preferred SoC at the end of the charging period. Therefore, each time-step should be scaled to a period between 1-3 minutes. A 1-minute interval was chosen to ensure that the battery charging would remain within the controllable range for the whole charging period.

6.4 RESULTS

Two sets of results for each experiment are shown.

i) For the first set, the micro-grid emulator provided by Tecnalia was used. This emulator is a piece of software that emulates the behaviour of the micro-grid devices.

ii) For the second set, the actual devices using the laboratory configuration presented in Fig. 6.5 were utilised.

In the laboratory, each experiment was executed twice to obtain the power demand profiles of a BEV and a PHEV from the EV-ON platform:

- The power demand profile when the EV agent was representing a PHEV that connects at 17:00.
- The power demand profile when the EV agent was representing a BEV that connects at 18:00.

These profiles were expected to be different due to the EV owners' preferences that were given as inputs.

- The charging profile of a BEV was expected to be stable because the initial battery SoC at the time of plugging-in would be approximately 30% and the desired SoC at the time of disconnection would be approximately 50%.
- The charging profile of a PHEV was expected to decrease after the third hour of charging as it would then enter the constant voltage charging state (i.e. the SoC would be more than 90%). A single set-point was applied by the EV agent at the beginning of each operational period, which is a similar approximation to the approximation made for the feeder loading (shown in Fig. 6.7 and Table 6.4).

Fig.6.8 to Fig. 6.12 show the test results. The measurements acquired from the actual DMMS300 measurement device were lower than the outputs from the micro-grid emulator in all experiments. This was due to the modelling assumption in the micro-grid emulator software that the voltage at the LV busbar of the laboratory switchboard (i.e where the measurement device is installed), is not affected by the demand of the loads connected to it. The actual voltage in the LV busbar of the laboratory switchboard was varying due to the load of the load banks and other loads of the lab.

6.4.1 Reference Case

A reference case is provided in Fig. 6.7 using calculations based on the lithium-ion battery characteristics provided in Appendix C and using the micro-grid emulator software. This case shows the feeder loading without the MAS control using the data presented in Section 6.3.1.

- The greyed area shows the feeder loading without EVs.
- The black dotted line shows the feeder loading limit.

- The grey line shows the feeder loading with EVs and no control.
- The black line shows the loading of the simulated feeder, as measured by the measurement device using the micro-grid emulator software. This line shows that the loading of the feeder would be relatively stable during each operational period. The small continuous variations are perturbations modelled in the micro-grid emulator software to consider voltage fluctuations.

The difference between the calculated values (grey line) and the micro-grid emulator output values (black line) in Fig. 6.7 is due to the single command sent to the load banks at the beginning of each operational period. When during an operational period the EV battery charging entered the constant voltage charging state (i.e. in case the SoC is above 90%), the load banks steps were not altered to reflect the equivalent load decrease. This was due to the limited time chosen for each time-step of the simulation. Ten measurements per minute were acquired from the measuring device (i.e. one measurement every six seconds). The process that would be needed to achieve the exact loading conditions every six seconds is:

- Ask each EV agent to report the power draw.
- Add the power demand from each EV agent to create aggregate demand.
- Calculate the appropriate steps for each load bank that are required to achieve the aggregate demand.
- Send command signals to the load banks for switching.

This process required more than six seconds in the single computer that was hosting all the agents and the communication software. However, the SoC of each EV agent was calculated considering the modelled charging characteristic. This approximation did not affect the testing of the MAS operation.

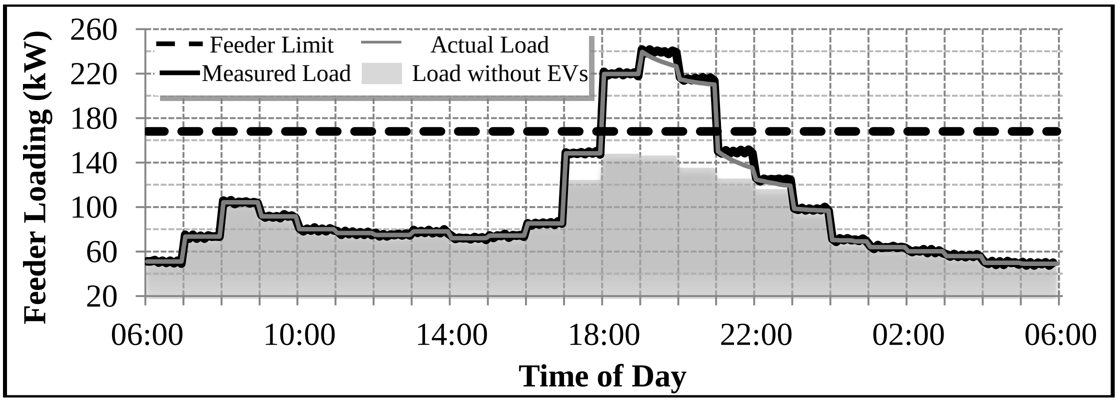


Fig. 6.7 Feeder loading with EV battery charging without control

Fig. 6.7 shows that if the battery charging of EVs was left uncontrolled and the charging process would start as soon as the EVs were plugged-in, the feeder loading limit would be exceeded. According to the assumptions presented in Table 6.3, each EV would require 6.5 kWh of net energy, therefore the 32 EVs would require 208kWh at the end of the simulated day.

Table 6.5 shows the total energy required by the EVs based on the modelled lithium-ion battery including the charging losses of the chargers and the batteries (grey line of Fig. 6.7) and the total energy as measured by the emulator's measurement device (black line of Fig. 6.7).

Table 6.5 Energy requirements for EV battery charging in the reference case study

Net EV energy requirement	Supplied EV energy requirement (calculated)	Supplied EV energy (measured by the emulator software)
208 kWh	282.38 kWh	313.14 kWh

6.4.2 Experiment 1

Fig. 6.8 shows the feeder loading and the EV-ON power demand when the MAS was operated under normal operating conditions with the policy of price following.

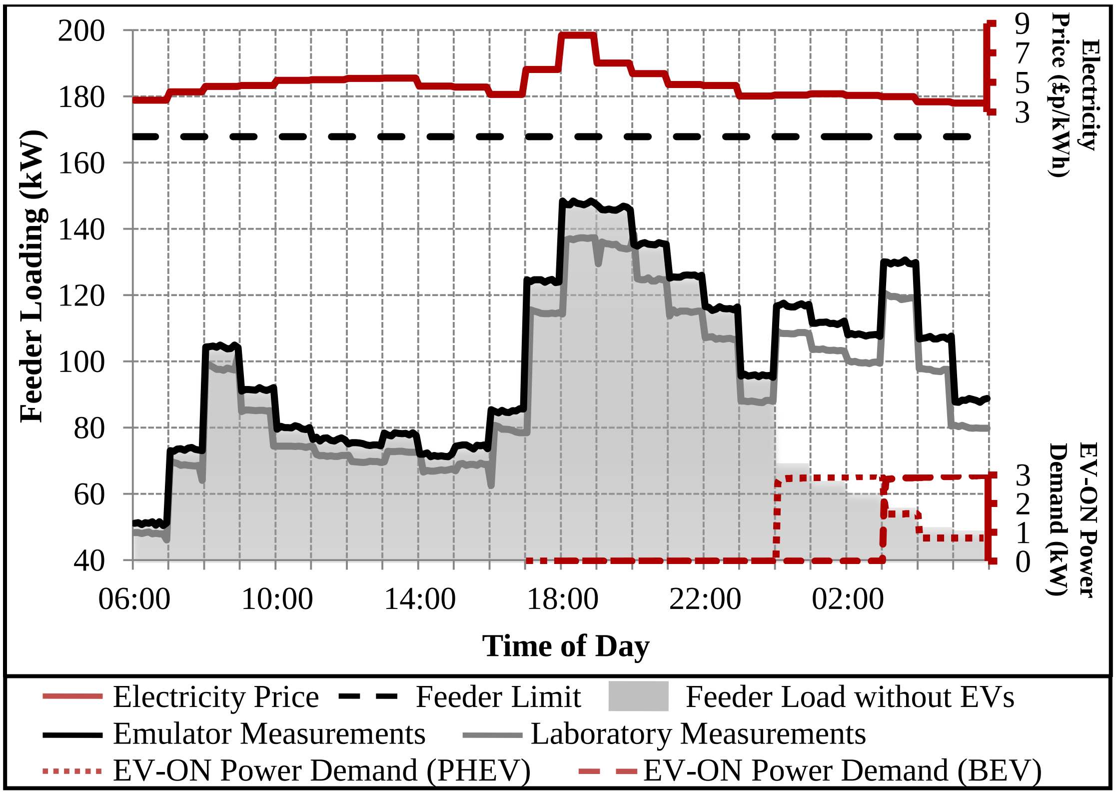


Fig.6.8 Feeder loading and EV-ON power demand measurements for price following under normal operating conditions

- The battery charging of EVs occurred during the cheapest hours of the period that the EVs were connected.
- The feeder loading limits were not violated.
- The preferences of all EV owners were satisfied.
- The energy supplied to the EVs was 314.12kWh.

6.4.3 Experiment 2

Fig. 6.9 shows the feeder loading and the EV-ON power demand when the MAS was operated under normal operating conditions aiming to reduce the EV load demand during the period 03:00-04:00. This is the period when the EV load demand was at maximum in Experiment 1. This condition was simulated by setting the electricity price signal for the specific hour to the highest value. It is shown that:

- The EV load demand is displaced at previous hours following the electricity prices.
- The feeder loading limits were not exceeded.
- The preferences of all EV owners were satisfied.
- The energy supplied to the EVs was 326kWh.

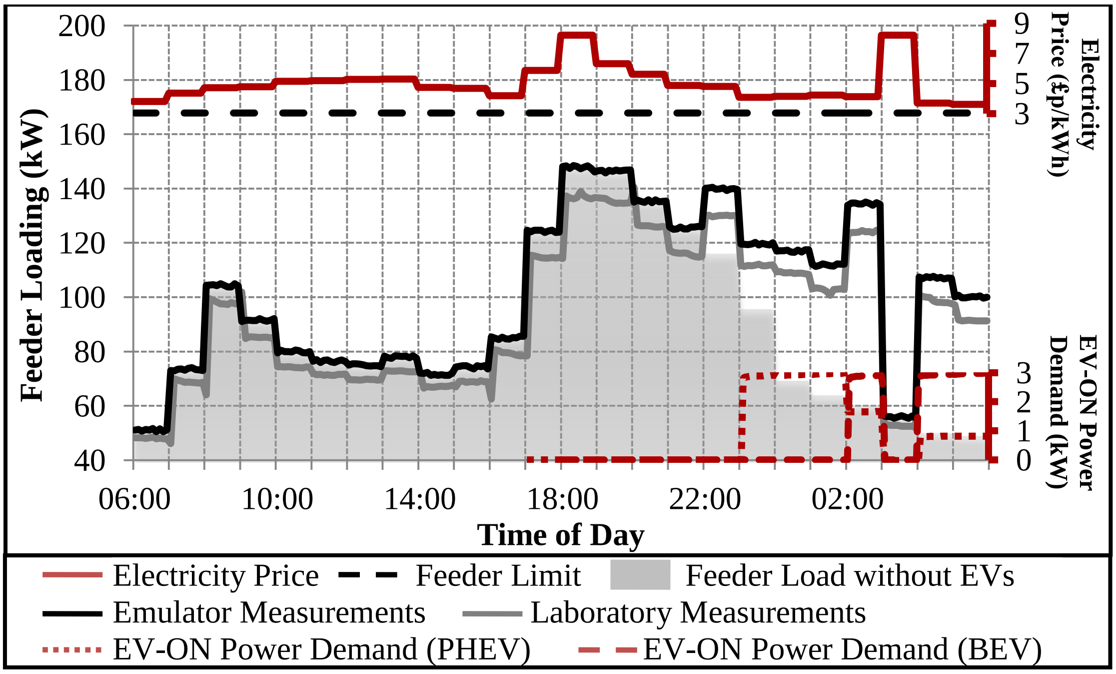


Fig. 6.9 Feeder loading and EV-ON power demand measurements for price following with demand reduction policy under normal operating conditions

6.4.4 Experiment 3

Fig. 6.10 shows the feeder loading and the EV-ON power demand when the MAS was operated under normal operating conditions allowing EVs to provide power back to the grid (V2G operation). This condition was simulated by setting the price for selling energy back to the grid at three times higher than the price for buying electricity from the grid. This arbitrary assumption was made because the battery utilisation cost for all EV agents was set to 6.027 £p/kWh. This number is calculated assuming 1000 full battery charging/discharging cycles as the battery life and an 85% average battery efficiency (see Fig. E.1, Appendix E).

In the experiment it was shown that the batteries from BEVs:

- During the first two operational periods of their connection, they would provide power back to the grid.
- During the third operational period, they would remain idle.
- During the fourth operational period they would be charged.
- During the fifth operational period they would be discharged.
- Finally their charging would remain at maximum until the end of the simulated day to fulfil the final SoC preference.

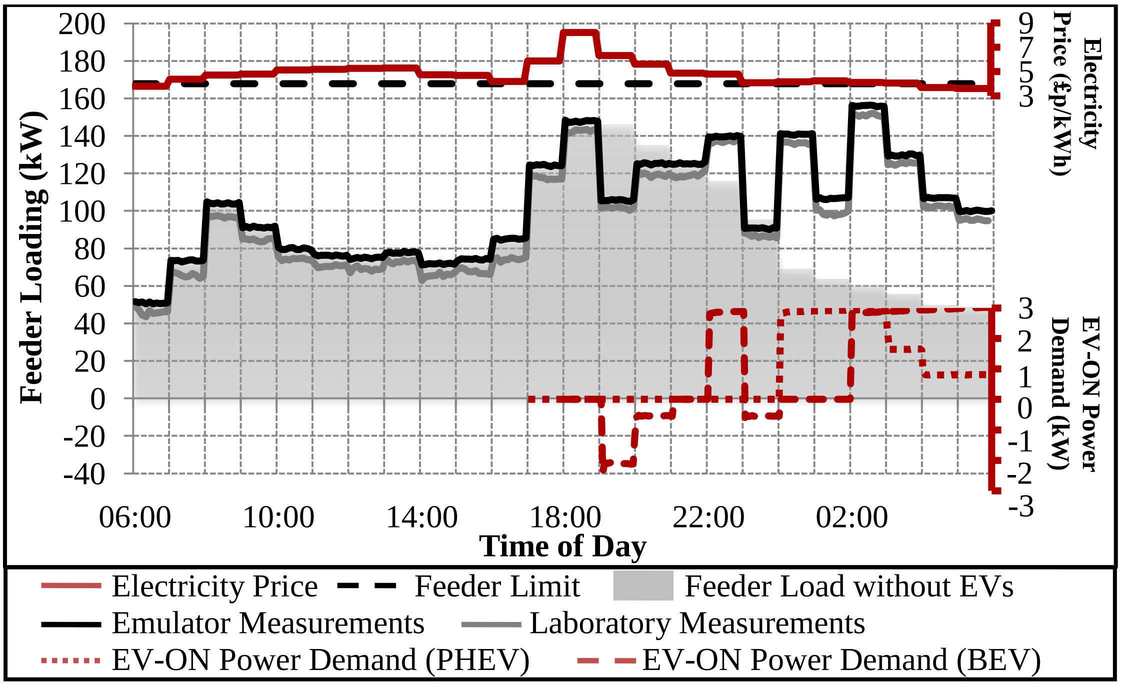


Fig. 6.10 Feeder loading and EV-ON power demand measurements for price following with V2G policy under normal operating conditions

The batteries from PHEVs would be charged with the same pattern as in Experiment 1 without providing power back to the grid, because there was not sufficient battery capacity and time to provide power back to the grid and then re-charge to a 100% SoC.

The experiment showed that:

- The preferences of all EV owners were satisfied.
- The feeder loading limits were not exceeded.
- The net energy supplied to the EVs was 358.26kWh.

6.4.5 Experiment 4

Fig. 6.11 shows the feeder loading and the EV-ON power demand when the MAS operation was tested for a technical invalidation from the DSO agent. This means that the set-points for an operational period were not validated during the planning period by the DSO agent.

This condition was created by setting manually the load forecasting output of the DSO agent to a value of 110kW for the operational period of 04:00-05:00. This change is shown in Fig. 6.11 with the dark red area.

The value of 110kW was chosen because, under normal operating conditions as shown in Fig. 6.8, the EV aggregate load demand during this period was approximately 60kW. Thus, the total feeder demand with the manual increase of 110kW, would be raised to a value of approximately 170kW, causing a feeder limit breach. This is shown in Fig. 6.11 with the orange line.

To acquire the EV-ON power demand profiles, the LA agent was manually forced to re-schedule the EV agent adapted to the EV-ON platform before the others. This resulted in the LA agent choosing the second profile from its priority list. This profile had a zero set-point for the operational period of 04:00-05:00 because the electricity price for this period was higher than the electricity price of the following period.

The experiment showed that:

- The operation of the MAS sustained the feeder loading within its limits.
- The preferences of three EV owners were not satisfied.

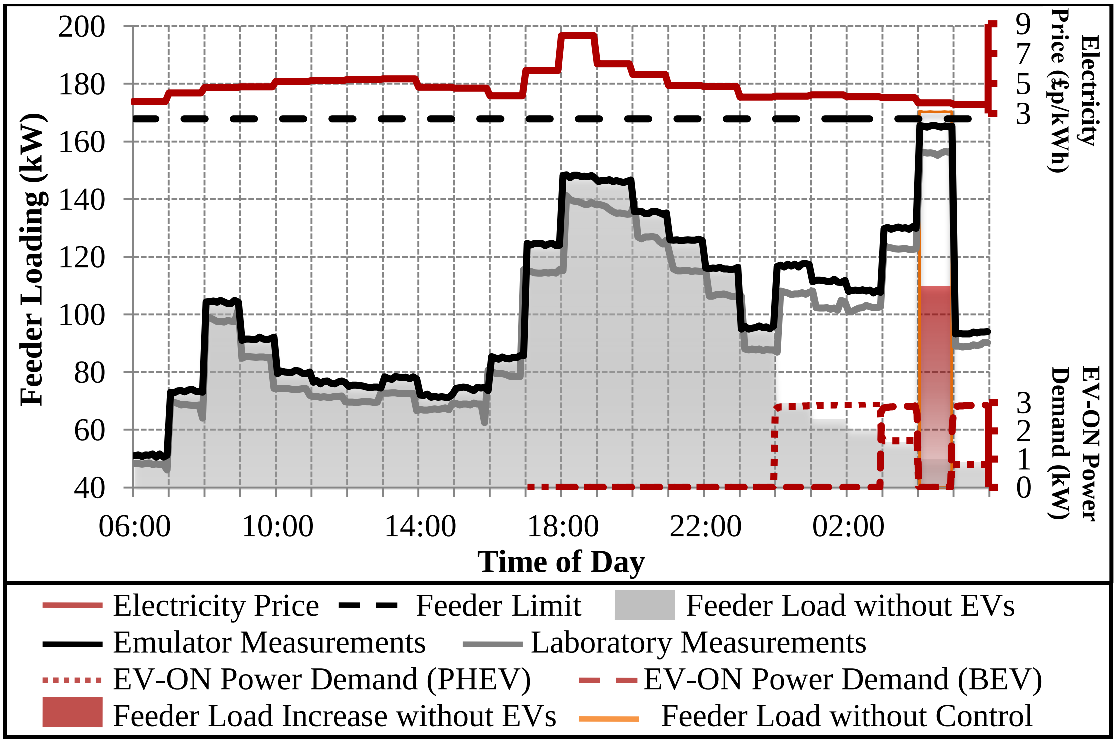


Fig. 6.11 Feeder loading and EV-ON power demand measurements for price following under technical invalidation from the DSO agent

1) When the EV agent of the EV-ON platform was representing a BEV, the final SoC of the BEV that was rescheduled was 15.85kWh instead of 17.7kWh which was the preferred SoC at the end of the connection duration. The final SoC of the remaining two PHEVs that were rescheduled was 8.7kWh and 8.68kWh instead of 9kWh which was the preferred SoC at the end of the connection duration. The energy supplied to the EVs as measured by the emulator software was 315.82kWh. This case is shown in Fig. 6.11 with the grey line.
2) When the EV agent of the EV-ON platform was representing a PHEV, all three EV agents that were re-scheduled were representing a PHEV. The final SoC of the three PHEVs that were rescheduled were 8.69kWh, 8.71kWh and 8.71kWh instead of 9kWh which was the preferred SoC at the end of the connection duration. The energy supplied to the EVs as measured by the emulator software was 318.15kWh. This case is omitted from Fig. 6.11 due to its similarity to the previous case.

6.4.6 Experiment 5

Fig. 6.12 shows the feeder loading and the EV-ON power demand when the MAS operation was tested during an emergency event.

A. Experiment using the micro-grid emulator software

The emergency condition was created by increasing the feeder loading manually to a value of 110kW after the start of the operational period of 04:00-05:00. This increase is shown with the dark red area in Fig. 6.12. The increase caused a feeder limit breach. The DSO agent detected the violation and the equivalent load of three PHEVs was curtailed. These PHEVs had the lowest risk factors. The final SoC of the three PHEVs were 8.85kWh, 8.9kWh and 8.91 kWh instead of 9kWh which was the preferred SoC at the end of the connection period. The energy supplied to the EVs as measured by the emulator software was 327.49kWh.

B. Experiment using the actual laboratory devices

The emergency event was created by increasing the feeder loading manually to a value of 120kW after the start of the operational period of 04:00-05:00. This increase is shown with the dark grey-red area in Fig. 6.12. To acquire the EV-ON power demand profiles, the risk factor of the EV agent that was adapted to the platform was manually set to 0 for the operational period of 04:00-05:00. This resulted in the DSO agent choosing the specific agent for curtailment. The manual load increase caused a feeder limit breach. However:

- The operation of the MAS restored the feeder loading within its limits.
- The preferences of three EV owners were not satisfied.

1) When the EV agent of the EV-ON platform was representing a BEV, the DSO agent detected the violation and the equivalent load of the BEV was curtailed. This curtailment was not adequate to restore normal operating conditions and the equivalent load of a PHEV was further curtailed. The final SoC of the BEV was 16.9kWh instead of 17.7kWh which was the preferred SoC at the end of the connection duration. The final SoC of the PHEV was 8.91kWh instead of 9kWh which was the preferred SoC at the end of the connection period.
2) When the EV agent of the EV-ON platform was representing a PHEV, the DSO agent detected the violation and the equivalent load of this PHEV was curtailed. This curtailment was not adequate to restore normal operating conditions and the equivalent load of two more PHEVs was curtailed based on the risk factors. The final SoC of the three PHEVs was 8.85kWh, 8.9kWh and 8.92kWh instead of 9kWh which was the preferred SoC at the end of the connection period.

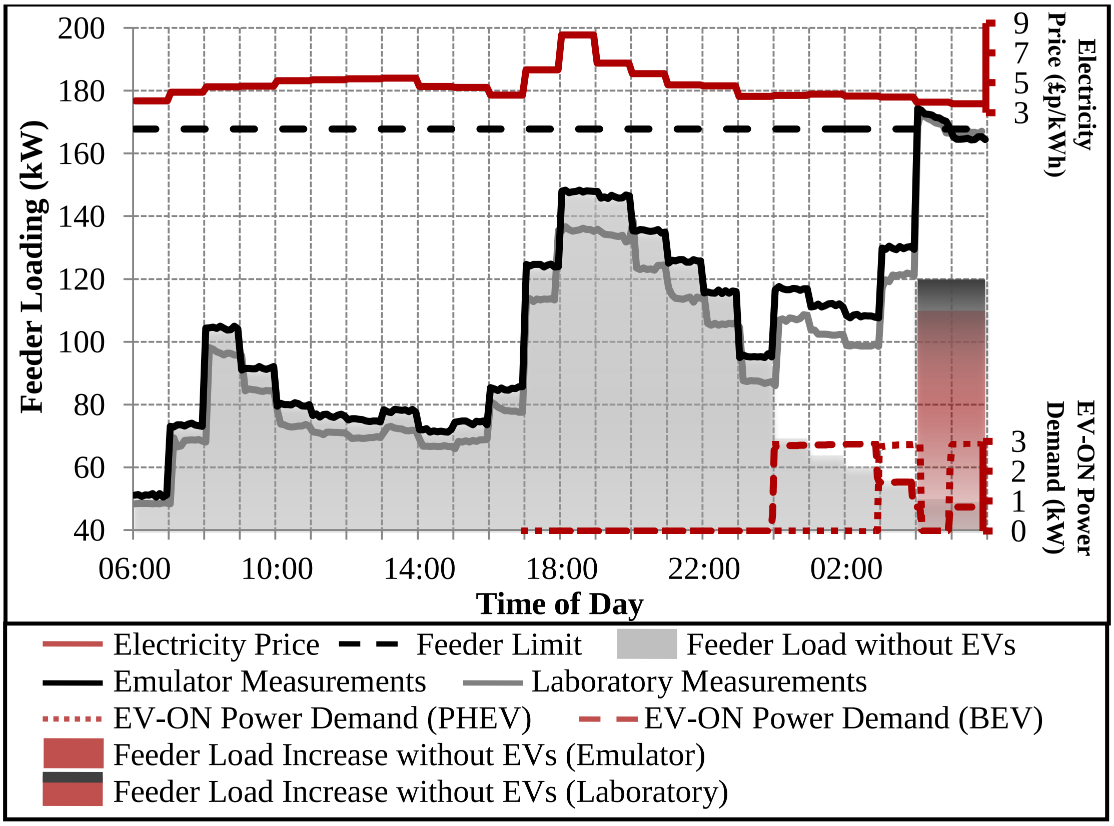


Fig. 6.12 Feeder loading and EV-ON power demand measurements for price following under emergency operating conditions

6.5 SUMMARY

The hierarchical Multi-Agent System (MAS) described in Chapter 5 was tested experimentally in the laboratory facilities of Tecnalia. An equivalent of a LV feeder was set-up that serves 96 residential customers based on the UK generic distribution network described in Chapter 4. This feeder was assumed to have 32 charging points with an equal number of EVs uniformly distributed among its nodes. 32 EV agents were assumed to represent 32 EV owners and were managed under a Local Aggregator (LA) agent that was assumed to be installed at a MV/LV substation level. The LA agent was managed by a Regional Aggregator agent that was communicating with the DSO representative agent.

Five experiments were conducted to evaluate the MAS operation. The experiments were firstly executed using software that emulates the behaviour of the laboratory devices. Thereafter, the experiments were re-run using the physical equipment to validate the simulation results.

Three of the experiments evaluated policies/control strategies when the electrical network was operated within its technical limits. One experiment evaluated the operation of the MAS during a foreseen load increase in the short term (i.e. technical invalidation from the DSO agent). One experiment evaluated the operation of the MAS during an unforeseen load increase in real-time (i.e. emergency condition).

The main findings from the MAS testing are:

- The ability of the MAS to **coordinate** EV battery charging within electrical network operating limits following electricity market price signals has been proven.
- The ability of the MAS to **respond** to **foreseen** short-term (i.e. the hour before energy delivery) network loading changes and act autonomously to adapt to these changes was shown. The constraints of the electrical network and the EV owner preferences were satisfied.
- The ability of the MAS to **respond** to real-time **emergency** events and act autonomously to restore normal operating conditions for the electrical network was shown.
- The ability of the MAS to operate using limited computational resources was shown. All the agents were running on a single computer.

CHAPTER 7

CONCLUSIONS AND SUGGESTIONS FOR FURTHER WORK

Electric Vehicles are anticipated to gain a significant share of the vehicle market in the forthcoming years. Formal EV uptake targets have not been set by the UK government. However, in document [255] that was published for the Committee on Climate Change, it is suggested that in order to decarbonise the transport sector and achieve the EU_{27} target of $95gCO_2$/km by 2020, 1.7 million EVs should be on British roads.

7.1 THESIS CONTRIBUTION

The contributions that were made in this thesis are summarised:

- Different electric vehicle charging regimes and uptake levels were used to evaluate the impact on grid demand at the national levels of Great Britain and Spain for the year 2030.
- The impact of electric vehicle battery charging on distribution network steady state voltage, thermal loadings of transformers and cables, and power line losses was addressed. A deterministic approach and a probabilistic approach were utilised to evaluate these impacts using computer simulations with a UK generic distribution network model.
- An agent-based control system for the coordination of EV battery charging on distribution networks was designed and developed.
- The agent-based control system was tested experimentally.

7.2 ELECTRIC VEHICLE BATTERY CHARGING IMPACT ON GRID DEMAND

In document [4] that was published for the British government, the average electricity demand required to cover the EV battery charging was calculated. The effect of EV battery charging on grid demand peaks was left open for investigation.

7.2.1 Summary of Research Work

Chapter 3 of this thesis investigated the effect of residential EV battery charging on grid demand peaks for the national systems of Great Britain and Spain. A case study for the year 2030 was defined. Two EV uptake levels were used, based on the scenarios developed in document [4]. A low EV uptake would be approximately 7% of the car fleet and a high EV uptake would be 48.5% of the car fleet. The same EV uptake levels were used for Spain, and the effect of residential EV battery charging on grid demand peaks at the national systems of Great Britain and Spain was investigated. Four EV charging regimes were applied:

1. Uncontrolled regime in which the battery charging of EVs would occur as soon as the EV owners return home: For the low EV uptake, the winter grid demand peak of GB would be increased by 5% and the winter grid demand peak for Spain would be increased by 7%. For the high EV uptake, the winter grid demand peak of GB would be increased by 60% and the winter grid demand peak for Spain would increase by 54%.

2. Dual tariff regime in which the battery charging of EVs would occur overnight: For the low EV uptake, the winter grid demand peak of GB would remain the same and the winter grid demand peak for Spain would be increased by 3.1%. For the high EV uptake, the winter grid demand peak of GB would be increased by 58.2% and the winter grid demand peak for Spain would increase by 77.1%.

3. Variable price regime in which the battery charging of EVs would occur during the cheapest hours of the day: For the low EV uptake, the winter grid demand peak of GB would be increased by 2.3% and the winter grid demand peak for Spain would be increased by 1.5%. For the high EV uptake, the winter grid demand peak of GB would be increased by 60.7% and the winter grid demand peak for Spain would be increased by 41.1%.

4. Mixed charging regime which combines in equal shares the uncontrolled, dual tariff and variable price regimes: For the low EV uptake, the winter grid demand peak of GB would be increased by 2.3% and the winter grid demand peak for Spain would be increased by 2.4%. For the high EV uptake, the winter grid demand peak of GB would be increased by 16.1% and the winter grid demand peak for Spain would be increased by 38.1%.

7.2.2 Limitations and Suggestions for Further Work

The study presented in Chapter 3 investigated the effect on grid demand from EV battery charging for a worst case for the grid:

- All EVs for both EV uptake levels investigated, were assumed to charge on the same day using residential outlets or charging points. Diversity on EV availability and other locations of charging were not considered.
- The batteries of the EVs were assumed to be at a minimum possible SoC before connecting to the grid (i.e. at 20% SoC) and charge until the time of disconnection.

The results for the high EV uptake showed that the grid demand would be greatly increased. The great increase in demand would affect the electricity market prices and hence a feedback on prices should be considered.

7.3 Electric Vehicle Battery Charging Impact on Power Distribution Networks

The loading capacity of power distribution networks is limited by the equipment rating, such as distribution transformers and cables, and operational parameters such as voltage on distribution feeders. Electricity demand for residential use is generally increasing and residential battery charging of EVs, will increase it further. In document [4], it is stated that "*the impact of vehicle charging on local networks and infrastructure is a critical area for study in future pilot and demonstration projects*".

7.3.1 Summary of Research Work

Chapter 4 of this thesis investigated the effect of EV battery charging on distribution network voltage, distribution transformer and cable loading, and electrical line losses. A case study for the year 2030 was built based on EV uptake levels of document [4]. The EV uptake levels correspond to 12.5%, 33% and 71% of the residences having an EV and were described as low, medium and high EV uptake levels. A residential UK LV generic distribution network model was used and two approaches were utilised:

1. A deterministic approach used load flow snapshots with a uniform distribution of EV loads across the nodes of a typical UK distribution network.
2. A probabilistic approach was employed to address behavioural uncertainties of EV owners, residential customers and micro-generation power outputs, types and installation locations. A dedicated software tool was designed and developed for the probabilistic simulations.

The results from the deterministic and probabilistic studies showed good agreement for the impact studies on distribution transformer and voltage profiles on distribution feeders. A disparity between the two approaches was observed in the study of cable loading and electrical losses due to the uncertainties considered in the probabilistic approach. The uncertainties included in the probabilistic approach showed that non-uniform distribution of EV load among network nodes and the temporal load variations would result in increased currents flowing through the cable emanating from the LV busbar. The probability of cable overload and the electrical line losses of the studied LV area would be increased.

A distribution network reinforcement approach was investigated. It was found that a low EV uptake level may be integrated without violating the operating limits of he network constraints studied, by upgrading underground cables and distribution transformers. This solution was found not to be enough for medium and high EV uptake levels. Micro-generators installation was found to overcome all the constraints for the medium EV uptake level. For the high EV uptake level the transformer loading and the voltage limits were not violated applying both the network reinforcements and the micro-generation installation.

A smart charging function was created and incorporated in the probabilistic algorithm. This function uses a simple heuristic to evaluate the effect of EV battery charging re-scheduling. For the case studies performed, the fraction of EVs for each uptake level allowing smart charging was varied from 0% to 100% in steps of 25%. The results with micro-generation sources and smart charging showed that a high penetration level of micro-generation (equivalent to approximately 18%) and smart control of EV battery charging would reduce the impact of the studied parameters.

7.3.2 Limitations and Suggestions for Further Work

Real-world data of EV usage are anticipated to become publicly available from pilot projects such as the plugged-in places in the UK [256]. From such data, probability density functions may be extracted to model the connection time and duration of EVs, and be integrated in the probabilistic software tool.

The centralised smart charging control function used in the probabilistic approach uses a simplified heuristic rule. The memory requirements and computation time may increase significantly with the increase of control variables (i.e. EVs whose charging can be re-scheduled). Tools such as multi-period power flows with the use of global optimisation algorithms should be used to quantify the amount of EVs that can be safely integrated in a distribution network.

7.4 COORDINATION OF ELECTRIC VEHICLE BATTERY CHARGING USING A MULTI- AGENT SYSTEM

The deployment of DER including electric vehicles will begin a change of distribution networks and utilities towards a smarter grid where increased use of monitoring systems and decision making tools for DER control will be needed. It was shown in Chapter 4 that only by reinforcing the distribution network will not be adequate to charge EV batteries within distribution network limits for a high EV uptake. Active network management techniques and methods are currently encouraged by regulators in order to enhance the performance of LV networks that are presently operated passively. In recent years, the technology of agents and Multi-Agent Systems has been developed and started to be applied in power system applications that require real-time monitoring and control, and some degree of autonomy.

7.4.1 Summary of Research Work

Chapter 5 of this thesis investigated the application of Multi-Agent Systems for the coordination of EV battery charging in LV distribution networks. Controllers that would be hierarchically located in a power distribution network were modelled as software agents.

The hierarchy of the Multi-Agent System and an algorithm that calculates the distribution network loading limits (named network limits matrix algorithm) were developed in collaboration with a colleague PhD student, I. Grau.

Four types of agents were developed:

1. A Regional Aggregator agent that would be located in the primary substation level.
2. A Local Aggregator agent that would be located in the secondary substation level.
3. An Electric Vehicle agent that would be located in the EV.
4. A DSO agent that would be located at the primary substation.

Information flows between the agents and the algorithms for their internal logic were designed and developed. The MAS is able to coordinate EV battery charging when:

1. The distribution network is operated within its technical limits (i.e. voltage of network nodes is within limits and distribution transformers and cables are not overloaded).
2. The distribution network suffers from voltage limits violations of transformer and cable overloads. In this case, the developed MAS is able to restore normal operating conditions by curtailing the charging of EV batteries.

7.4.2 Limitations and Suggestions for Further Work

The developed MAS comprises hierarchical agents with decision making processes being split between them and decisions are made in a cooperative way. The EV agents provide the Local Aggregator agent with a set of alternatives (plausible charging schedules), and the Local Aggregator agent decides the EV set-points based on a simplified economic evaluation for each LV feeder. It was assumed that the EV owners that would commit to this management program, would be compensated in the case the schedules chosen would lead to some EVs charging during more expensive hours than others.

The technical and economic performance of the proposed concept should be evaluated and compared with:

- A game theory decentralised approach in which EV agents compete for energy trading. This may be done by setting-up local markets and designing EV agents with abilities for forecasting and decision making for bidding.
- A centralised approach in which decisions are taken centrally taking under consideration a wider set of power system variables. This may be done by transferring a set of preferences and characteristics from each EV agent to a central scheduler. Thereafter, optimal power flow software could be used to obtain optimal actions.

7.5 EXPERIMENTAL EVALUATION OF THE MULTI-AGENT SYSTEM

The algorithms of the agent-based system presented in Chapter 5 were evaluated individually for each agent at a modelling level. The adaptation of the agents to a real physical environment would prove that the MAS is able to work under real-world conditions.

The laboratory facilities of Tecnalia including the micro-grid emulator, communication software, and the expertise of staff in real-world DER applications, were used for validation of the agent-based system.

7.5.1 Summary of Research Work

A residential feeder of the UK LV generic distribution work was emulated in the laboratory of Tecnalia using two resistive load banks. One measurement device was used to acquire measurements and transfer them to the agent-based system. One EV agent was adapted to the EV-ON platform, a cluster of hardware and software resources that mimics the behaviour of an actual EV.

Three tests were conducted to test the MAS during normal operating conditions:

1. Minimise the cost of charging complying with the technical limits of the network.
2. Minimise the cost of charging complying with the technical limits of the network, and aiming to minimise the EV load demand during a particular period.
3. Minimise the cost of charging complying with the technical limits of the network, allowing power injections from the EVs back to the grid during a particular period.

Two tests were conducted to test the MAS under the conditions of experiment one mentioned above, creating artificially the following events:

1. Evaluate the behaviour of the system during a foreseen load increase in the short term.
2. Evaluate the behaviour of the system during an unforeseen load increase in real-time.

It was concluded that the MAS was able to achieve its design objectives for all experiments conducted.

7.5.2 Limitations and Suggestions for Further Work

The battery used in the EV-ON platform was lead-acid technology based battery. The battery modelled in the EV software agent that was adapted on the EV-ON platform was a lithium-ion battery. Further work should include testing of the charging and discharging behaviour of a real lithium-ion battery. Thereafter, detailed modelling of real battery characteristics should be incorporated into the EV agent and the experiments using the real lithium-ion battery should be conducted with the operation of the whole MAS.

The experiments conducted for the artificially created unplanned events revealed that although the priority of the MAS to coordinate EV battery charging within network technical constraints was satisfied, some of the EV owner preferences were not fulfilled. This means that the battery SoC at the end of the connection period was not the desired one. It was assumed that in such case compensation would be provided by the DSO. A security loading capacity margin should be considered in the network limits matrix in order to avoid this case.

Additional EV battery charging policies for the MAS could be designed. When EV load data become available, predictions that will allow market participation of the aggregator will be needed. EV load prediction tools will be required. These prediction tools may use data from different areas to create compound EV load demand profiles for energy trading. In that case, the following functions should be developed in the proposed MAS:

- Minimise the battery charging of EVs within network technical constraints aiming to follow a day-ahead compound EV load demand profile for a single LV area.

- Set-up information exchange between different Local Aggregator agents to minimise the imbalances of a given compound EV load demand profile for a large geographical area under the management of the Regional Aggregator agent.

7.6 OVERALL RESEARCH BENEFIT

A number of actors could benefit from the work provided in this thesis.

1. Overall this research may provide insights for **regulators** to formulate and promote policies that will accelerate the uptake of electric vehicles and other low carbon technologies. In collaboration with distribution system operators, standardisation bodies and local councils, a push towards charging infrastructures installations for electric vehicles and incentives for EV ownership may be achieved. From a policy perspective, revisions for services companies such as aggregators should take under consideration the efficiency and reliability improvements, and the business potential that may be offered.
2. **Distribution system operators** may benefit from this research with regards to the impacts that are anticipated from EV utilisation on steady-state operational parameters of their networks. The impact studies conducted and the control approaches simulated and evaluated showed some of the benefits that active management approaches may offer, in contrast to the present passive operation of distribution networks.
3. **Society and the environment** may generally benefit from this research. The management of EV battery charging and possible introduction of new tariffs for EVs may yield to deferral of costly infrastructural updates of distribution networks and enhance the energy consumption awareness of customers. Therefore, economic benefits may be seen and overall, carbon dioxide emissions reductions may be achieved.

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[254] N2EX, Nord Pool Spot, Nasdaq OMC Commodities, [Online]: Available at: http://www.n2ex.com/, [Accessed 26 September 2011].

[255] Committee on Climate Change, "Meeting Carbon Budgets –ensuring a low-carbon recovery.2nd Progress Report to Parliament", 2010, [Online]: Available at:http://downloads.theccc.org.uk.s3.amazonaws.com/0610/CCC-ProgressReport-web-version_3.pdf, [Accessed 26 September 2011].

[256] Department for Transport (DfT), "Plugged-in places", [Online]: Available at: http://www.dft. gov.uk/topics/sustainable/olev/recharging-electric-vehicles/, [Accessed 26 September 2011].

APPENDIX A

RESILIENT PROPAGATION ALGORITHM FOR ARTIFICIAL NEURAL NETWORK TRAINING

The resilient propagation algorithm is reported in [178], as a fast and efficient propagation technique for training Multi-Layer Perceptron Artificial Neural Networks. This section describes the algorithm in brief.

When the algorithm is initiated, small random numbers are assigned to the synaptic weights. The training error between the desired and the actual outputs is calculated. The training iterations continue for the whole training dataset, until the gradient of the average error falls below a predefined threshold [172]. At each iteration the weights are updated.

In resilient propagation, each synaptic weight is updated based on rule (A.1).

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} * \Delta_{ij}^{(t-1)}, & \text{if } \dfrac{\theta E}{\theta w_{ij}}^{(t-1)} * \dfrac{\theta E}{\theta w_{ij}}^{(t)} > 0 \\ \eta^{-} * \Delta_{ij}^{(t-1)}, & \text{if } \dfrac{\theta E}{\theta w_{ij}}^{(t-1)} * \dfrac{\theta E}{\theta w_{ij}}^{(t)} < 0 \\ \Delta_{ij}^{(t-1)}, & \text{else} \end{cases} \qquad (A.1)$$

Where

$\Delta_{ij}^{(t)}$ is the updated value for the synaptic weights *i* to *j* for iteration *t*

$\Delta_{ij}^{(t-1)}$ is the updated value for the synaptic weights *i* to *j* for iteration *t-1*

E is the training error

η is a factor where $0 < \eta^{-} < 1 < \eta^{+}$

$\dfrac{\theta E}{\theta w_{ij}}^{(t)}$ is the gradient weight for the synaptic weights *i* to *j* for iteration *t*

$\dfrac{\theta E}{\theta w_{ij}}^{(t-1)}$ is the gradient weight for the synaptic weights *i* to *j* for iteration *t-1*

The rule A.1 means that "*every time the partial derivative of the corresponding weight* w_{ij} *changes its sign, which indicates that the last update was too big and the algorithm has jumped over a local minimum, the update-value* Δ_{ij} *is decreased by the factor* η. *If the derivative retains its sign, the update-value is slightly increased in order to accelerate convergence in shallow regions*" [178]:

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)} & , \text{ if } \dfrac{\theta E^{(t)}}{\theta w_{ij}} > 0 \\ +\Delta_{ij}^{(t)} & , \text{ if } \dfrac{\theta E^{(t)}}{\theta w_{ij}} < 0 \\ 0 & , \text{ else} \end{cases} \tag{A.2}$$

"*Once the update-value for each weight is adapted, the weight-update follows a simple rule: if the derivative is positive, i.e. the error has increased, the weight is decreased by its update-value, if the derivative is negative, the update-value is added*" [178].

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)} \tag{A.3}$$

In the case that there is a change in the sign of the derivative, the previous weight-update is reverted and the $\dfrac{\theta E}{\theta w_{ij}}^{(t-1)}$ is set to zero in equation (A.2) to avoid repetition [178].

Improvements in speed of convergence of the resilient propagation algorithm are reported in [179]. The reversion of the previous weight-update, in the case that there is a change in the sign, is done only if the overall error E^t for the current iteration is higher than the error E^{t-1} of the previous iteration. The resilient propagation algorithm with this improvement is called improved resilient propagation +, or IPROP$^+$.

APPENDIX B

GRAPHICAL USER INTERFACE (GUI) OF THE DEVELOPED SOFTWARE FOR PROBABILISTIC SIMULATIONS

This section provides the graphical user interfaces developed for the dedicated software tool described in Chapter 4. With this software, probabilistic simulations may run to evaluate the impact of electric vehicles and micro-generation on the UK generic LV distribution network used in Chapter 4.

From the GUI shown in Fig. B.1 the type of simulation may be selected. Three types of simulations may be run from this tool:

- Single configuration simulation: in this type, EVs and mGen units are randomly placed throughout the nodes of the network and the Monte Carlo procedure is executed for the same configuration. This is a general simulation that aims to provide a first view of the impact on the distribution network studied parameters.
- Multiple configuration simulation: in this type, EVs and mGen units are randomly placed throughout the nodes of the network for every iteration of the Monte Carlo procedure. This type of simulation aims to provide a detailed view of the impact on the distribution network studied parameters.
- Specific configuration: in this type of simulation the user is able to place manually EVs and mGen in each node of the network. This type of simulation aims to provide the user with the ability to evaluate the impact on the distribution network studied parameters for any configuration is required.

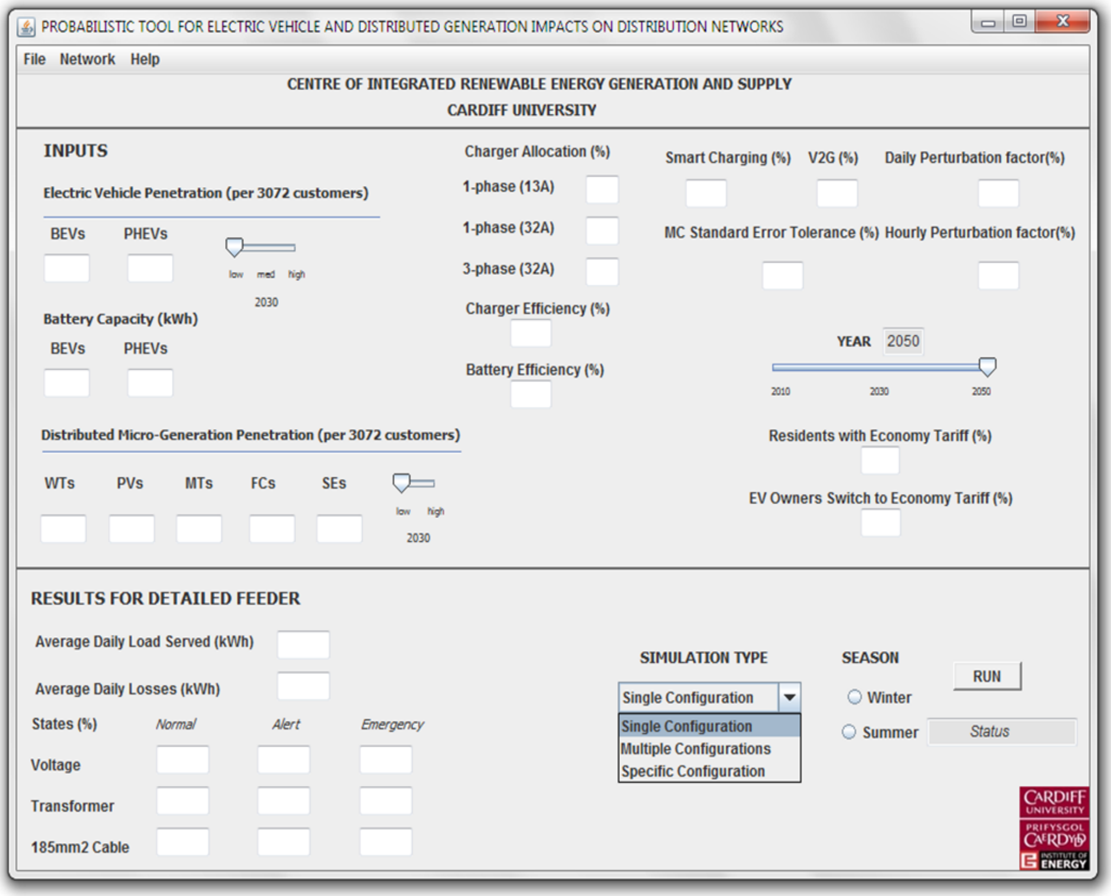

Fig. B.1GUI for selection of inputs and simulation type of the probabilistic software tool

In the case that specific configuration is chosen, two additional GUIs appear to allow the insertion of user inputs for each node of the LV network. In the first (Fig. B.2), inputs for the 3072 customers may be inserted. The mGen inputs for the detailed LV area are inserted separately. The EV inputs for the detailed LV area can be inserted from the GUI in Fig. B.3.

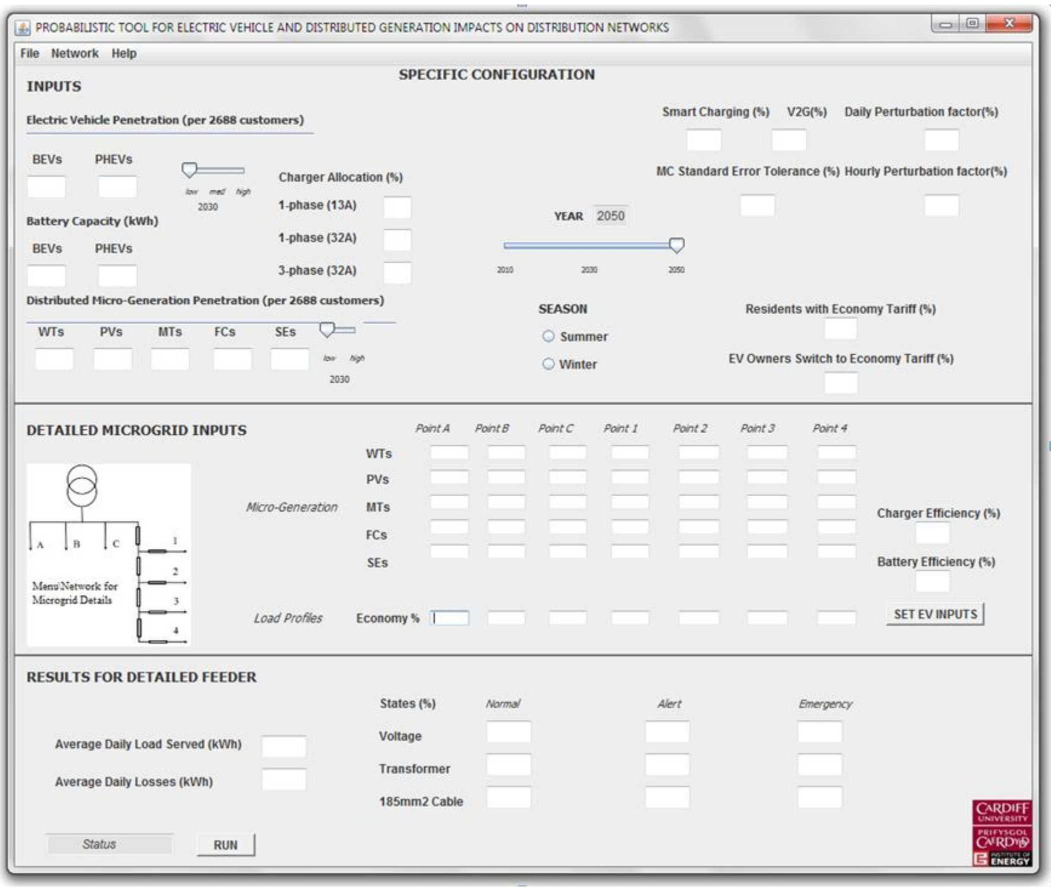

Fig. B.2 GUI for selection of user inputs in the specific configuration

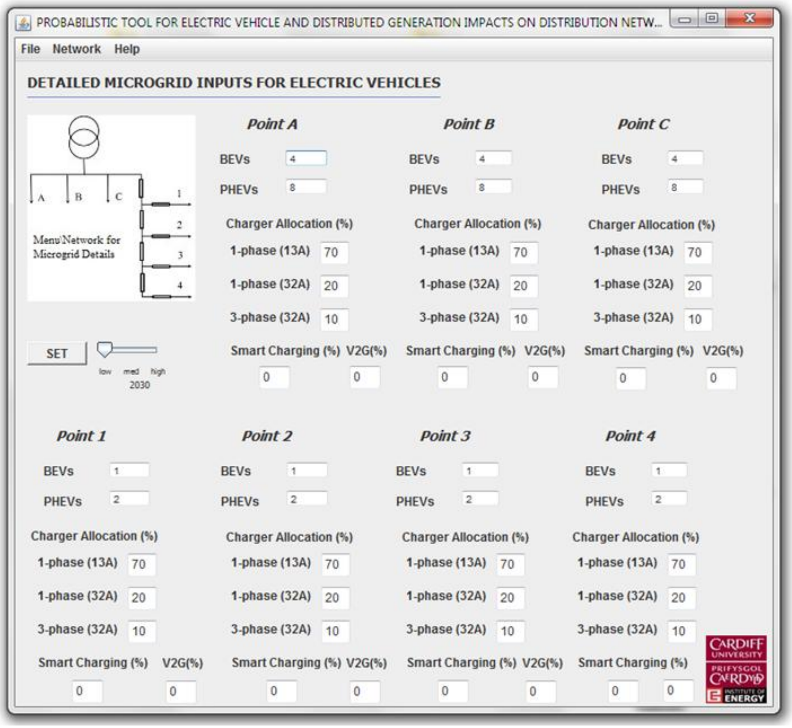

Fig. B.3 GUI for selection of user inputs for EVs in the specific configuration

APPENDIX C

DERIVATION OF PARAMETERS FOR LITHIUM-ION BATTERY CHARACTERISTICS

The parameters of a lithium-ion battery charging characteristic are estimated. These parameters are used to model a lithium-ion battery for the EV agent developed in Chapter 5 and tested in Chapter 6.

C.1 BATTERY CHARGING

The following characteristics were used to model the lithium-ion battery:

- Power characteristic: this characteristic is used to calculate the set-points for each time-step of the EV connection period.
- State of Charge (SoC) characteristic: this characteristic is used to estimate the SoC for each time-step of the EV connection period.

Both characteristics were deducted from the charging characteristic shown in Fig. C.1.

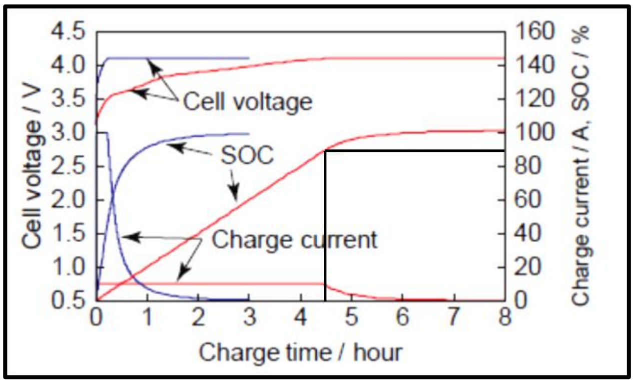

Fig. C.1 Representative charging characteristic of LEV50 type lithium-ion cells at 10A (—) and 100A (—) at 25 ºC [245]. The black solid lines show that when the cell reaches 90% SoC (in 4.5 hours from the beginning of charging with 0% SoC), then the current starts decreasing.

The battery model of the EV agent is assumed to comprise of modules whose cells exhibit the charging characteristic of Fig. C.1. The nominal charging current is assumed to be $I_{nominal}$ = 13A at 230V ($P_{nominal}$=2.99kW). The voltage of the charging point is assumed to remain constant at 230V.

The following assumptions are made, with deduction from Fig. C.1:

- The battery is fully charged from zero SoC in eight hours.
- From 0% SoC to 90% SoC:

  i) The charging current remains constant at 13A and the power at 2.99kW.

  ii) The SoC increases linearly based on equation (C.1):

$$SoC(t_s+t_c)= SoC(t_s) + P_{nominal} * e_B * e_C * t_c \qquad \text{(C.1)}$$

Where

SoC is the battery State of Charge (kWh),

t_c is the current point in time,

t_s is the time (hours) when SoC estimation is needed during the constant current charging range, with $0 \leq t_c \leq 4.5$,

e_B is the average battery efficiency,

e_{Cn} is the charger's efficiency at 13A.

- From 90% SoC to 100% SoC:

  i) The charging current decreases exponentially based on equation (C.2):

$$I\,(t_e) = I_{\,nominal} * e^{-at_e/3.5} \qquad \text{(C.2)}$$

Where

t_e is the time (hours) when current estimation is needed, during the exponential range with $0 \leq t_e \leq 3.5$,

a is a constant.

The constant a is calculated from equation (C.2) to 1.026 assuming that the charging current is 1A at the seventh hour of charging. The power characteristic for the case of battery charging is described by equation (C.3):

$$P(t)= \begin{cases} P(t_c)+P_{nominal}\ , \ \ if\ \ SoC<90\% \\ \\ P(t_c)+P_{nominal}*\, e^{-at}\ , \ \ if\ \ SoC>90\% \end{cases} \tag{C.3}$$

The Xantrex XW4024 hybrid charger/inverter used for the experimental validation of the MAS in Chapter 6, provides a number of available positive set-points. The set-point of 13A is included. For the set-points estimated when the battery SoC was in the region of 90%-100%, a lookup table was used with the set-points that the inverter is able to accept, and the closest value was chosen.

ii) The SoC increases exponentially based on equation (C.4):

$$SoC\ (t_e) = C_b*(1 - e^{-bt}) \tag{C.4}$$

Where

b is a constant.

The constant b is calculated from equation (C.4) to 0.033 assuming that the SoC is 98% at the seventh hour of charging. The SoC characteristic for the case of battery charging is described by equation (C.5):

$$SoC(t)= \begin{cases} SoC(t_s+t_c)=SoC(t_s)+(P_{nominal}*\, e_B*\, e_C\ *t_c)*(1+E_s), \\ if\ \ SoC<90\% \\ \\ SoC\ (t_e)=B_{cap}*(1\ \text{-}\ e^{-bt}\ )*(1+E_s),\ if\ \ SoC<90\% \end{cases} \tag{C.5}$$

Where

E_s is a SoC estimation error modelled as random number from a uniform distribution with a maximum of an absolute value of 0.05%.

For the experiments presented in Chapter 6:

- The average battery efficiency e_B was assumed 0.85, based on [76].
- The EV charger's efficiency e_C at 13A, was assumed 0.917. This value is the efficiency of the Xantrex hybrid inverter/charger XW4024 that was used in the laboratory of Tecnalia.

C.2 Battery Discharging

Battery discharging characteristics are not currently available in the literature for modelling the behaviour of a lithium-ion battery in V2G mode. The characteristics of the Xantrex hybrid inverter/charger XW4024 were used. Fig. C.2 shows that for different ranges of the battery SoC, a number of set-points may be applied. The horizontal axis shows the minimum SoC of the availability of these set-points. For example, for a battery SoC value higher than 50%, the range of acceptable current set-points are from -11.1A to -13.

It should be noted that the particular inverter may accept lower set-points down to -18A but in this thesis the lowest limit was assumed to be -13A.

The efficiency of the inverter differs for each set-point. The variation is analogous, i.e. the higher the set-point, the higher the efficiency. This is shown in Fig. C.3.

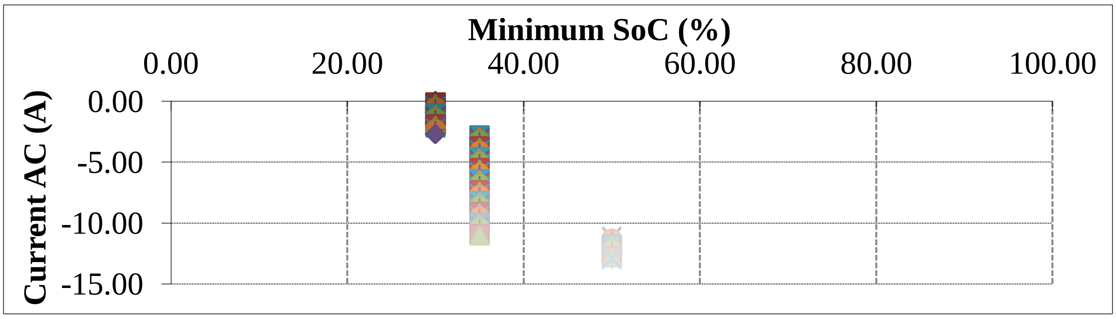

Fig. C.2 Range of acceptable set-points by the Xantrex charger/inverter XW4024 for different ranges of battery SoC

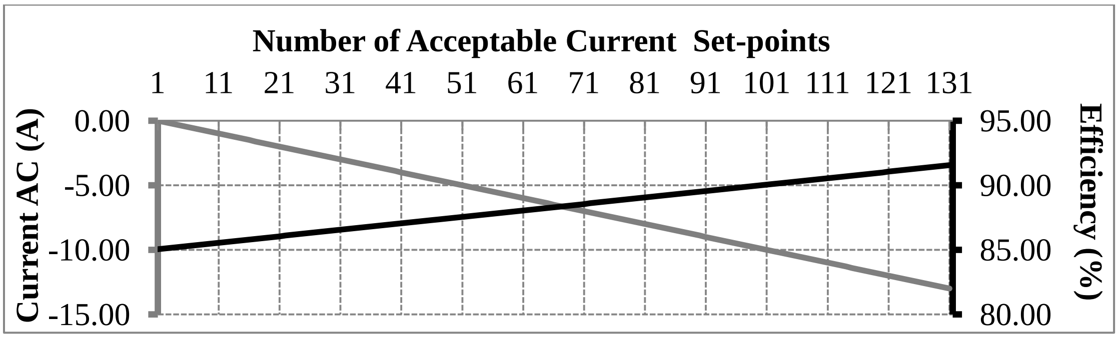

Fig. C.3 Relationship between current set-point (A) and efficiency (%) of the Xantrex XW4024 hybrid charger/inverter

It was assumed that the EV agent could apply only the set-points with the highest efficiency for each range of the battery SoC. This assumption was made to provide the most economical choices for the EV owner. Thus, three available set-points were inserted in the EV agent's logic for the planning algorithm, in the case of discharging:

$$I=\begin{cases} -12.97A, & if\ \ SoC \geq 50\% \\ -11A, & if\ \ 30\% \leq SoC < 50\% \\ -2.7A, & if\ \ SoC < 30\% \end{cases} \qquad (C.6)$$

The power characteristic used, assuming a constant single-phase voltage of 230V, is described by equation (C.7). The battery efficiency e_b was assumed stable at 85% throughout the discharging process.

$$P=\begin{cases} -2.98kW, & if\ \ SoC \geq 50\%,\ with\ e_c{=}91.55\% \\ -2.53kW, & if\ \ 30\% \leq SoC < 50\%,\ with\ e_c{=}90.55\% \\ -0.621kW, & if\ \ SoC < 30\%,\ with\ e_c{=}86.4\% \end{cases} \qquad (C.7)$$

The SoC estimation was performed using the rule described in equation (C.7) with an application of a SoC estimation error identical to the one provided in equation (C.5).

$$SoC(t)= SoC(t_s+t_c)=SoC(t_s)+(P^*\ e_B^*\ e_C\ ^*t_c)^*(1+E_s) \qquad (C.8)$$

C.3 BATTERY SELF-DISCHARGE

The self-discharge percentage of lithium ion batteries is reported to be less than 5% per month in [2,3] and approximately 2-3% in [4]. For the modelling of the self-discharge of a lithium ion battery in this thesis, a random number is chosen from the EV agent in the planning algorithm. This number is drawn from a uniform distribution with a minimum of 0% and a maximum of 0.005%. This translates to a monthly maximum self-discharge percentage of 3.6%.

[2] D., U., Sauer, "The battery – Bottleneck for the E-mobility?", Worksho of the the Dutch Royal Institute of Engineers, Available at: http://afdelingen.kiviniria.net/media-afdelingen/DOM100000139/Verslagen/01_-_Prof._Dirk_Uwe_Sauer_-_The_battery_Bottleneck_for_the_E-mobility.pdf, (last accessed: October 2011).
[3] Electronics Lab, "How to rebuild a Li-Ion battery pack", Implemented for Fujitsu - Siemens Lifebook S-Series FPCBP25 battery pack", Available at: http://www.electronics-lab.com/articles/Li_Ion_reconstruct/, (last accessed: October 2011).
[4] Electropedia, "Battery and energy technologies", Available at: http://www.mpoweruk.com/performance.htm, (last accessed: October 2011).

APPENDIX D

EXAMPLE AND EVALUATION OF BREADTH FIRST SEARCH ALGORITHM WITH PRUNING STEP

The criteria used in [121] to evaluate the performance of problem-solving algorithms are:

- Completeness: Is the algorithm guaranteed to find a solution?
- Optimality: Does the strategy find the optimal solution?
- Time complexity: How long does it take to find a solution?
- Space complexity: How much memory is needed to perform the search?

The BFS algorithm is reported in [121] to perform well with completeness and optimality but may require a large amount of resources in terms of memory and time of calculations. In the EV agent's problem, if the constructed search tree was uniform with a branching factor *b*=3 (one for each action; charging, idle and discharging), the cases that would have to be enumerated for a 24 hourly time-steps horizon are 3^{24}=282,429,536,481. These calculations would require 33 days and 282 Terabytes (TB) of memory, assuming that 100,000 nodes can be generated per second and each node requires 1000 bytes of storage [121].

To reduce the calculation time and the memory required for the calculation of feasible schedules, a pruning step was added to the breadth-first algorithm. This means that sub-trees that are not going to contain feasible schedules are not further expanded. A schedule is feasible when it satisfies a number of constraints. These constraints are evaluated per stage of the tree expansion.

D.1 Example of Breadth First Search with Pruning Step

The EV battery SoC in the hour T is SoC_T=3kWh and the desired SoC_{end} at the time of disconnection T+2 is SoC_d=5kWh. The possible energy exchange between the

EV battery and the grid at each time-step is E_x=2kWh. The EV agent's possible actions are charge, idle or discharge, therefore after the first time-step (T+1), the possible SoC of the EV battery would be SoC_T+E_x, SoC_T and SoC_T-E_x. For each action, the feasibility of the generated node is checked. In this example the only constraint is the minimum battery capacity SoC_{min}=1.5kWh. The node whose action is discharge at time-step T+1 is discarded because it does not satisfy the constraint (Fig. D.1).

The two nodes that satisfied the constraint are stored and the algorithm moves to the next time-step. After the second time-step (T+2), only two schedules satisfy the EV owner's desired SoC_d. These are the feasible EV charging schedules (Fig. D.2).

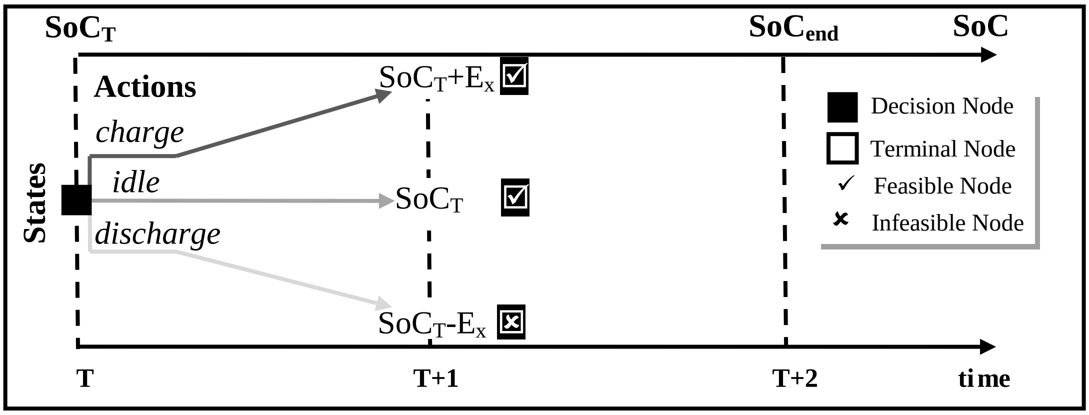

Fig. D.1 Planning algorithm's evolution after one time-step

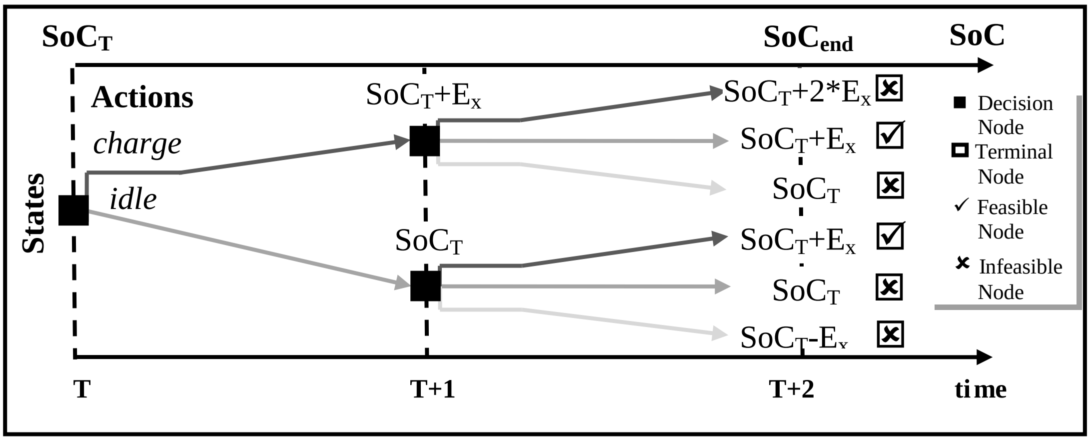

Fig. D.2 Planning algorithm's evolution after two time-steps

D.2 EVALUATION OF EV AGENT'S PLANNING ALGORITHM'S PERFORMANCE

The effect of the pruning step (i.e. insertion of constraints) in terms of calculation time and memory required, was investigated. The following case was evaluated:

- The EV owner allows power injections from the EV back to the grid: The branching factor is the highest possible, b=3.
- The connection period of the EV is the full horizon: 24 hourly time-steps.
- The electricity prices for selling power back to the grid are high: Three times the price for buying electricity.
- The battery SoC at the beginning and end of the connection period are the same, and equal to half of the usable battery capacity: 14kWh for a usable battery capacity of 28kWh.
- The battery utilisation cost was set to 6.027p/kWh assuming an average of 85% battery efficiency, 1000 cycles of battery life, a battery capital cost of 51.43£/kWh and an annual interest rate of 7.7%.
- The hourly electricity prices of all winter days for the winter of the year ending 2010 from [254], were averaged to create a single daily electricity price profile. These electricity prices were assumed for buying energy from the grid.

The algorithm was executed and the number of solutions found was 3,802,004. This calculation would require approximately 42 seconds and 3.8 Gigabytes (GB) of memory according to [121]. The calculation time and memory requirements were deemed adequate for the specific problem.

APPENDIX E

SENSITIVITY ANALYSIS OF LITHIUM BATTERY UTILISATION COST

The battery utilisation cost is the cost of use of an electric vehicle's battery to provide power back to the grid. This section shows that this cost varies greatly, depending on a number of factors.

Lithium-ion battery technologies are considered a strong candidate for use in electric vehicles. This is due to a number of advantages they offer[2]: lack of maintenance requirement due to sealed cells; long cycle life; broad temperature range of operation; low self-discharge rate; rapid charge capability; high rate and high power discharge capability; high efficiency; high specific energy and energy density; no memory effect.

To estimate the utilisation cost of providing power back to the grid, the factors considered in equations (5.3) and (5.4) in Chapter 5 are provided.

- Battery capital cost: this is the initial cost required to acquire the battery,
- Battery lifecycle: this is the duration of the useful life of a battery and it depends on a number of factors. These include[5,6] :
  i) The full charge/discharge cycles,
  ii) The environmental conditions such as temperature and humidity,
  iii) The charging behaviour of the EV owner, i.e. loss of capacity may occur if the battery is frequently overcharged or undercharged,
  iv) Daily use of battery.
- Battery efficiency.

[5] D. Linden, and T., B. Reddy, "Handbook of batteries", 2002, published by McGraw-Hill, ISBN 0-07-135978-8.S.
[6] Dhameja, "Electric vehicle battery systems", 2002, published by Newnes, Butterwoth-Heinemann. ISBN 0-7506-9916-7.

Projections for the battery capital cost, were aggregated in a study conducted for the EU funded project Grids for Vehicles[7]. This study reports current projections of a maximum 400 €/kWh, within a timeframe of the year 2030. A long term target of 65-80 €/kWh for the year 2030 is reported. With the current exchange rate of 1.15 (£/€), this translates to 56.5-69.5£/kWh. In document [4] prepared for the UK government, a capital cost of £1800 for a 35kWh battery in 2030 is assumed for the year 2030. This translates to 51.43£/kWh.

In order to account for the depreciation of the battery throughout the period of its use, an annual interest rate (discount factor) is used[8]. Fig. E.1 shows the variation of the battery utilisation cost based on the equations (5.3) and (5.4) using:

- a discount factor of 7.7%[9],
- a battery capital cost of 51.43£/kWh.

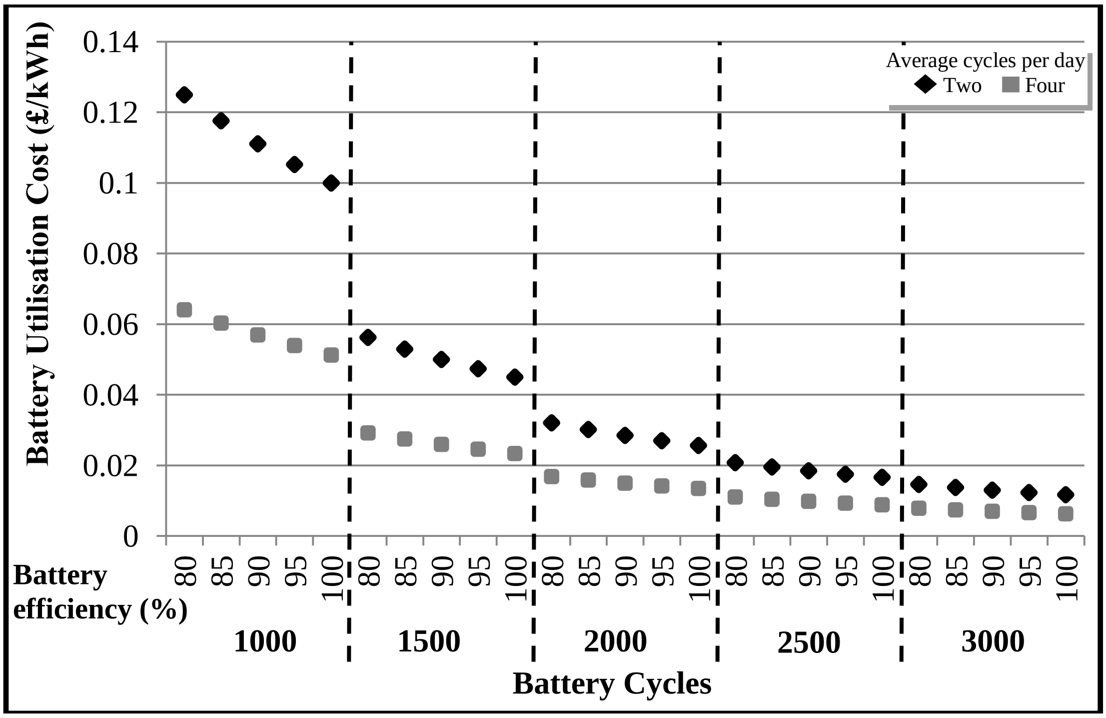

Fig. E.1 Sensitivity of battery utilisation cost to battery efficiency, full battery charge/discharge cycles and average battery full cycles per day

[7] http://www.g4v.eu/datas/Parameter_Manual_WP1_3_RWTH_101216.pdf

[8] W. Kempton and J. Tomić, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," Journal of Power Sources, vol. 144, pp. 268-279, 2005.

[9] U.S Department of Energy, "Annual energy outlook with projections to 2030", 2006. Last accessed: 15/10/2011: http://www.scag.ca.gov/rcp/pdf/publications/1_2006AnnualEnergyOutlook.pdf

APPENDIX F

EXAMPLE OF EV AGENT IMPLEMENTATION IN JADE

At the initiation of the EV agent the following three behaviours are uploaded in the behaviour pool after the EV agent registers to the Directory Facilitator.

- Planning period behaviour: this behaviour is executed when a message is received by the Local Aggregator agent that contains the hourly electricity prices for a whole day to start the planning period.
- Operational period behaviour: this behaviour is executed when a message is received by the Local Aggregator agent to start the operational period.
- Curtailment behaviour: this behaviour is executed when a message is received by the DSO agent to curtail the battery charging of the EV.

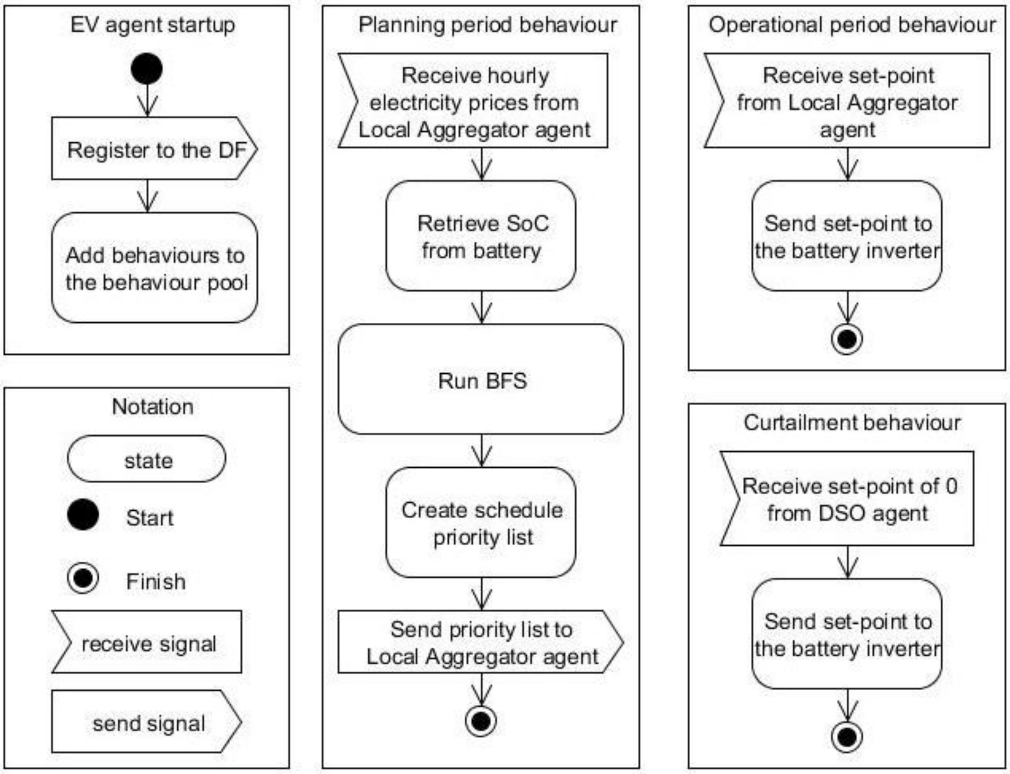

Fig. F.1 Activity diagram of the EV agent start-up and behaviours