Smart Management of the Charging of Electric Vehicles

THESIS SUBMITTED FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

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ABSTRACT

The objective of this thesis was to investigate the management of electric vehicles (EVs) battery charging in distribution networks.

Real EVs charging event data were used to investigate their charging demand profiles in a geographical area. A model was developed to analyse their charging demand characteristics and calculate their potential medium term operating risk level for the distribution network of the corresponding geographical area. A case study with real charging and weather data from three counties in UK was presented to demonstrate the modelling framework.

The effectiveness of a charging control algorithm is dependent on the early knowledge of future EVs charging demand and local generation. To this end, two models were developed to provide this knowledge. The first model utilised data mining principles to forecast the day ahead EVs charging demand based on historical charging event data. The performance of four data mining methods in forecasting the charging demand of an EVs fleet was evaluated using real charging data from USA and France. The second model utilised a data fitting approach to produce stochastic generation forecast scenarios based only on the historical data. A case study was presented to evaluate the performance of the model based on real data from wind generators in UK.

An agent-based control algorithm was developed to manage the EVs battery charging, according to the vehicles' owner preferences, distribution network technical constraints and local distributed generation. Three agent classes were considered, a EVs/DG aggregator and "Responsive" or "Unresponsive" EVs. The real-time operation of the control system was experimentally demonstrated at the Electric Energy Systems Laboratory hosted at the National Technical University of Athens. A series of experiments demonstrated the adaptive behaviour of "Responsive" EVs agents and proved their ability to charge preferentially from renewable energy sources.

DECLARATION

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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 ABBREVIATIONS

ANNs	Artificial Neural Networks
ac	Alternating Current
BAU	Business as Usual
BEVs	Battery Electric Vehicles
BMS	Battery Management System
CLNR	Customer Led Network Revolution
CO_2	Carbon Dioxide Emissions
CoG	Centre of Gravity
CSV	Comma-Separated Values
dc	Direct Current
DfT	Department for Transport
DG	Distributed Generation
DNO	Distribution Network Operator
DOD	Depth of Discharge
DOM	Degree-Of-Membership
DSL	Digital Subscriber Line
DSM	Demand Side Management
DSO	Distribution System Operator
EES	Electric Energy Systems
EVs	Electric Vehicles
EVSE	Electric Vehicle Supply Equipment
FCEVs	Fuel Cell Electric Vehicles
GHG	Greenhouse Gas Emissions

GPRS	General Packet Radio Service
GR	Growth Ratio
HEVs	Hybrid Electric Vehicles
HIL	Hardware-In-The-Loop
HuT	Hardware Under Test
ICE	Internal Combustion Engine
KDD	Knowledge-Discovery-From-Databases
LP	Linear Programming
LV	Low Voltage
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAS	Multi-Agent Systems
MDP	Markov Decision Process
ME	Mean Error
MIL	Model-In-The-Loop
MLP	Multi-Layered Perceptron
MV	Medium Voltage
NCR	National Charging Registry
NMAE	Normalised Mean Absolute Error
NTUA	National Technical University of Athens
OLEV	Office for Low Emission Vehicles
PAR	Peak-To-Average Ratio
PDF	Probability Density Function
PHEVs	Plug-in Hybrid Electric Vehicles
PiM	Plugged-in Midlands

PLC	Power Line Communication
PV	Photovoltaic
RBF	Radial Basis Function
REP	Reduced Error Pruning
RES	Renewable Energy Sources
RMSE	Root Mean Square Error
RTDS	Real Time Digital Simulator
SDE	Standard Deviation of Errors
SOC	State of Charge
SOH	State of Health
SVM	Support Vector Machines
ToU	Time-of-Use
UK	United Kingdom
USA	United States of America
V2G	Vehicle-To-Grid
V2V	Vehicle-To-Vehicle

CHAPTER 1

INTRODUCTION

1.1 ELECTRIC VEHICLES DEFINITIONS

Electric Vehicles (EVs) are automobiles which their motion is supported by an electric engine. EVs are classified in three categories: i) Fuel Cell Electric Vehicles (FCEVs), ii) Battery Electric Vehicles (BEVs) and iii) Hybrid Electric Vehicles (HEVs). In this classification, vehicles with a permanent cabled connection to the grid such as trams are excluded.

Each type of EVs absorbs the necessary energy for its driving needs from a different power source. Fuel cells supply energy to FCEVs while batteries provide power to BEVs. HEVs are composed of an Internal Combustion Engine (ICE) and an electric engine and thus the power source of the corresponding engines are fossil fuels and batteries. In addition, HEVs with the capability to recharge their battery from the electricity grid are referred to as Plug-in Hybrid Electric Vehicles (PHEVs).

This thesis considers only BEVs and PHEVs which electricity supplied by the electric power system is used to recharge their batteries. If not mentioned otherwise, in this thesis the term EVs will refer to these two types of battery EVs.

1.2 IMPACTS OF EVS CHARGING ON DISTRIBUTION NETWORKS

Road transport is a significant contributor to greenhouse gas emissions (GHG) and reductions are required for moving United Kingdom (UK) to a low carbon future in order to meet the Climate Change Act targets, based on UK Department for Transport (DfT) [1]. The electrification of transport offers a good opportunity to decrease carbon dioxide emissions (CO_2) and increase the national energy security.

Governments and local authorities provide incentives to EVs owners aiming to boost EVs adoption by decreasing the total cost of ownership of EVs compared to conventional ICE vehicles. The financial incentives, in combination with a potential increase in the oil prices, lead customers to consider EVs as a reliable and economical solution for transportation.

The development of an EVs market is strongly dependent on the parallel development of the recharging infrastructure which will result in a spatially uneven increase in the electricity demand. The UK government supports the penetration of ultra-low emission vehicles by announcing recently a £37 million funding package for providing 75% of the cost of installing new charging points in order to motivate the EVs drivers to reduce their range anxiety.

EVs are a mobile source of demand, charged for relatively long periods of time and as a result of this, EVs could place significant coincident demand on the system. The uncontrolled charging of EVs might increase the system's peak demand, exceeding voltage limits and/or overloading lines and transformers [2], [3]. When higher level of EVs penetration is considered, such phenomena are more often and intense [4]. If all the registered vehicles in United States had to charge 5-10kWh on a daily basis, this would lead to an increase of 12-23% at the electricity generation requirement [5]. In UK, an uncontrolled EVs charging regime increases the British winter day peak demand by 3.2 GW (3.1%) for a low EVs uptake case (7%) and the British winter day peak demand by 37GW (59.6%) for a high EVs uptake case (48.5%), for the year 2030 [6], [7].

In order to maintain the normal operation of the power grid, the generation capacity must be increased to meet this new additional demand of EVs charging. Equipment, especially in the existing distribution and transmission networks, will be overloaded and this may affect the stability and reliability of the power system. It is anticipated that the system may face voltage-drops, power losses increase and overloading of distribution transformers [7]. The impact of EVs charging is significant for the Distribution Network Operators (DNOs) as there is a need to manage the line congestion and voltage drops [6]. The future electricity networks will also have to integrate distributed generators, as well as energy storage and adapt to new types of demand in addition to the need to power EVs [8]. Network reinforcement is one solution to cope with the large deployment of EVs, however this solution is expensive. An alternative way is to integrate smart grid control techniques which avoid large investments on the electricity grid.

1.3 THESIS OBJECTIVES

The key question that this thesis aims to address is how electric vehicle battery charging can be managed to be integrated in distribution networks.

To answer this question, the following objectives were set:

i. Design and develop a risk assessment framework for identifying the risk level of EVs charging demand in a geographical area.
ii. Design and develop forecasting techniques which can be used in the smart management of EVs charging.
iii. Design and develop a scheduling algorithm for the coordination of EVs battery charging.
iv. Demonstrate experimentally the performance of the charging control algorithm in a micro-grid laboratory.

1.4 THESIS CONTRIBUTIONS

The main contributions of this thesis regarding the smart management of the charging of EVs are summarised below:

i. A complete data analysis framework for handling real EVs charging data was proposed. This analysis determines the relative risk of EVs charging demand among different geographical areas and defines the necessity for a charging control algorithm.
ii. Two forecasting methods were developed to be used in the smart management of EVs charging. These methods aim to forecast the day-ahead EVs charging demand and the day-ahead local

distributed generation (DG). Their outputs improve the performance of a charging control model.

iii. A control algorithm to manage EVs charging demand was developed utilising the future knowledge of EVs battery charging and local DG.

iv. The performance of the charging control algorithm was demonstrated through simulation and experimental case studies.

1.5 LIST OF PUBLICATIONS

The research work described in this thesis has been accepted for publication or published in the following peer-review journals and conference papers:

Journal Papers

i. Xydas, E., Marmaras, C., Cipcigan, L. M., Jenkins, N., Carroll, S., & Barker, M. (2016). *A data-driven approach for characterising the charging demand of electric vehicles: A UK case study*. Applied Energy, 162, 763-771.

ii. Xydas, E., Marmaras, C., & Cipcigan, L. M. (2016). *A multi-agent based scheduling algorithm for adaptive electric vehicles charging*. Applied Energy, 177, 354-365.

iii. Xydas, E., Qadrdan, M., Marmaras, C., Cipcigan, L. M., Jenkins, (2016), *Probabilistic Wind Power Forecasting and its Application in the Scheduling of Gas-fired Generators*. Accepted at Applied Energy.

Book Chapters

iv. Xydas, E., Marmaras, C., Cipcigan, L. M., & Jenkins, N. (2015). *Smart management of PEV charging enhanced by PEV load*

Forecasting. In Plug In Electric Vehicles in Smart Grids (pp. 139-168). Springer Singapore.

<u>Conference Papers</u>

v. Xydas, E. S., Marmaras, C. E., Cipcigan, L. M., Hassan, A. S., & Jenkins, N. (2013, September). *Forecasting electric vehicle charging demand using support vector machines*. In Power Engineering Conference (UPEC), 2013 48th International Universities' (pp. 1-6). IEEE.

vi. Xydas, E. S., Marmaras, C. E., Cipcigan, L. M., Hassan, A. S., & Jenkins, N. (2013, November). *Electric vehicle load forecasting using data mining methods*. In Hybrid and Electric Vehicles Conference 2013 (HEVC 2013), IET (pp. 1-6). IET.

1.6 THESIS STRUCTURE

This thesis is structured as follows:

Chapter 2: The relevant literature used in the thesis is presented. An overview is given with regards to: a) the smart management of the charging of EVs, b) charging control architecture types, c) charging control strategies, d) charging control techniques.

Chapter 3: A characterisation framework for EVs charging demand is presented. A data analysis methodology is used to extract information hidden behind charging events in order to identify the characteristics of the EVs charging load. This information is then used by a fuzzy based characterisation model to estimate the underlying relative risks for the distribution networks among different geographical areas independently to their actual corresponding distribution networks. The framework is applied on a dataset of real charging events from three counties in UK and their “risk level” index is calculated.

Chapter 4: Two forecasting models which can be used for the smart management of EVs charging are presented. The first model utilises data mining principles in order to forecast the day-ahead charging demand of EVs. The performance of four data mining methods in forecasting the charging demand of an EVs fleet is evaluated using real EVs charging event data. The second model is used to produce day-ahead stochastic forecast scenarios for the local DG in a geographical area. The impact of frequent updating of the forecasts is investigated using a rolling forecasting approach. A case study is presented to evaluate the performance of the forecasting model using times series of real wind power data from wind generators in UK.

Chapter 5: A decentralised algorithm to manage the EVs charging schedules, enhanced by EVs load forecast is presented. The aim of the control algorithm is to achieve a valley-filling effect on the demand curve, avoiding a potential increase of the peak demand. In this control algorithm, a realistic scenario for the future composition of the EVs is considered. EVs are separated in "Responsive" and "Unresponsive" to control signals coming from an aggregator. The importance of forecasting the charging demand of EVs to the control algorithm is illustrated through simulation case studies.

Chapter 6: An improved version of the decentralised scheduling algorithm for EVs charging presented in Chapter 5 is described in Chapter 6. Their main difference is the additional capability of the advanced model to coordinate EVs charging in order to maximise the use of the local DG for the EVs charging. The performance of the advanced control algorithm is experimentally demonstrated at the Electric Energy Systems (EES) Laboratory hosted at the National Technical University of Athens (NTUA). The results showed the adaptive behaviour of "Responsive" EVs agents and proved their ability to charge preferentially from Renewable Energy Sources (RES).

Chapter 7: The main conclusions of this thesis are summarised. Suggestions for further work are also given.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Due to environmental concerns and energy security issues, the EVs car sales is anticipated to increase in the following years. A large deployment of EVs will lead to lower GHG, fuel efficiency, oil independency and increased penetration of renewable energy. Road transport today is dominated by oil-delivered fuels and ICE vehicles and such a high level of dependence on one single source of primary energy carries strategic, climatic and economic risks.

Electric mobility offers an opportunity for diversification of the primary energy sources used in transport, but also brings new risks, technological challenges and commercial imperatives. Depending on the location and the times the EVs are plugged in, they could cause local constraints on the grid. For the extreme scenario of the penetration of EVs in Great Britain in 2030, it is estimated that the electricity demand will increase by 59.6 percent [7].

The integration of EVs is considered as a promising alternative to reduce transportation related emissions and improve energy consumption efficiency. However, EVs may not reduce GHG emissions unless the carbon intensity of electricity sector is improved [9]. Charging EVs from RES (e.g. solar, wind) may contribute to achieve environmental benefits.

Changes in the electricity demand will occur as a result of the EVs uptake. Due to the temporal and spatial variability of EVs charging energy patterns, the load demand at the national level is expected to increase. The impacts of EVs charging in distribution networks create higher power peaks, overload power transformers, causing voltage drops and line over-loading [10]–[12].

Demand Side Management (DSM) is seen as an effective solution to address these challenges in the existing distribution networks. EVs offer opportunities for effective DSM, utilising their flexibility with regards to the time of charging. Therefore, EVs charging management is a potential solution to shift charging demand based on the renewable energy production or to shift charging to off peak hours, decreasing voltage fluctuation and transformer loading.

The philosophy of adapting power demand to power generation is applied to maintain the normal operation of the electricity grid. Coordinating EVs charging is an effective and low cost solution to reduce the impacts of this additional electricity demand on the electric power systems. The majority of EVs owners are expected to plug in their vehicles in the evening hours when they return home after work. They would like to have their vehicles fully charged the next day in the morning when they go to work. Considering the fact that no less than 90% of the cars are parked during the day, there is opportunity to shift the electricity consumption from EVs charging to times with lower demand [7]. Smart charging control algorithms make use of this flexibility in order to reduce peak loads or charge EVs preferentially from RES. These algorithms define the charging schedules of EVs based on their objective (e.g. valley-fill, peak shaving, and frequency regulation).

Due to the EVs impact on distribution networks, EVs charging control models have attracted substantial research attention. Each charging control model is slightly different in terms of specific attributes and geographical area applications. The main differences are related to the (i) decision level of charging, (ii) existence of forecasting actions, (iii) implementation techniques used for solving the charging scheduling problem, (iv) strategy goal, (v) type of constraints, and (vi) option of utilising EVs battery as a storage unit via (Vehicle-To-Grid) V2G operation.

2.2 CHARGING CONTROL MODEL ENTITIES

EVs management schemes consist mainly of two type of entities, the EVs aggregator and the individual EV. The EVs aggregator represents an energy market entity which can manage the EVs charging demand directly or indirectly. In some cases, the EVs aggregator can also manage small scale renewable energy generation in a geographical area, and utilises the flexibility from EVs to consume this generation locally. The EVs are entities representing the EVs owner’s preferences and their rational behaviour. There are two types of EVs aggregators:

i. Commercial aggregator: The objective of the aggregator is to minimise the cost of charging.
ii. Technical aggregator: The objective of the aggregator is to optimise the operation of the grid.

In [13] and [14], a technical aggregator was used to manage the EVs charging for technical objectives and in particular to:

i. Minimise system losses
ii. Peak shaving
iii. Line Congestion management and voltage regulation
iv. Maximise power delivered within defined time intervals

For the technical aggregator, information regarding the network topology including the location of generators, non-EVs loads and EVs are assumed to be known in advance.

In [15] and [16] commercial aggregator was used to manage the EVs charging for commercial objectives and in particular to:

i. Minimise the EVs charging cost
ii. Enabling market participation

For a commercial aggregator, information regarding electricity wholesale prices, electricity tariff zones and other service revenues agreements are assumed to be known on a day-ahead basis.

2.3 CHARGING CONTROL ARCHITECTURE

The charging control models are classified in centralised and decentralised based on the decision making entity which controls the charging schedules.

2.3.1 Centralised Charging Control

A centralised control approach is applied to a system when the intelligence is gathered in one central unit and this unit controls the actions of all the other components of the system. The central control unit is responsible to manage the EVs charging demand, controlling directly the charging process of each EVs. The EVs aggregator sends control signals to every EV individually, containing information for its own charging schedule. EVs obey at the control signal and charge based on the generated charging schedules. The EVs aggregator calculates the EVs charging schedules, based on its control strategy and objectives. This is achieved by calculating the impact of a charging schedule on the aggregated charging demand. The main assumptions used for the centralised management of the EVs charging are:

i. The EVs aggregator defines the individual charging schedules of each EV and then EVs charge based on the control signals broadcasted by the EVs aggregator.
ii. The EVs aggregator has knowledge about the EVs owner preferences regarding desired SOC when plug out, charger power ratings as well as the arrival and departure time.
iii. The daily profiles for the non-EVs load demand and generation are known. These are reported as the outputs of forecasting models.

A main drawback of centralised control, is that the computational complexity, information exchanges and required communications links are increasing with large populations of EVs. The centralised control strategy requires high computational power and communication links as the number of EVs is increasing, making this strategy inappropriate for large population of EVs. Centralised control approaches are found to perform well for a limited number of EVs. While the number of EVs is increasing, the interactions between EVs and the central aggregator become more complicated. This bi-directional communication requires a large amount of data to be acquired and processed from a central unit, increasing the minimum requirements of the computational resources [17]. Figure 2.1 shows the architecture of centralised charging control approach.

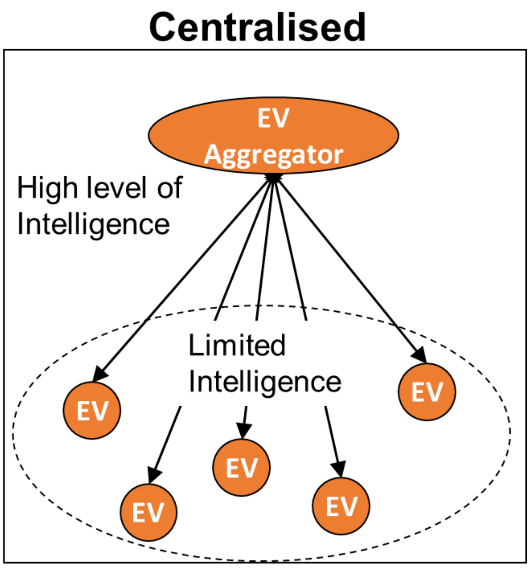

Figure 2.1: Architecture of a Centralised Charging Control

2.3.2 Decentralised Charging Control

In a decentralised control approach, the intelligence is distributed among the components of the system. In a decentralised charging control approach, decision making processes are done both from the EVs aggregator and EVs. Based on the level of the decentralisation, a decentralised charging control model can be further classified as fully decentralised and hierarchical decentralised.

In a fully decentralised charging control approach, EVs define their own charging schedules dependent on the signals received from the EVs aggregator. In a hierarchical decentralised charging control approach, intermediate aggregation layers exist between the EVs aggregator and the EVs. Similar to the fully decentralised approach, EVs define their own charging schedules based on signals received from the EVs aggregator located at the above aggregation layer.

In decentralised charging control algorithms, the charging decisions are taken by EVs, by having knowledge of the local condition of the distribution network and involves less communications.

The main assumptions used for the decentralised management of the charging of EVs are:

i. The EVs aggregator broadcasts control signals based on its objectives. Each EV is defining its individual charging schedule aiming to fulfil its own goals. This results indirectly in achieving the global objectives of the charging management system.
ii. The EVs aggregator does not have knowledge about the EVs owner preferences.
iii. When considered, the daily profiles for the non-EVs load demand and generation are known. These are reported as the outputs of forecasting models.

In contrast, the effectiveness of the distributed control techniques is independent to the number of EVs, as each EVs solves the scheduling problem individually. Figure 2.2 shows the architecture of decentralised charging control approach.

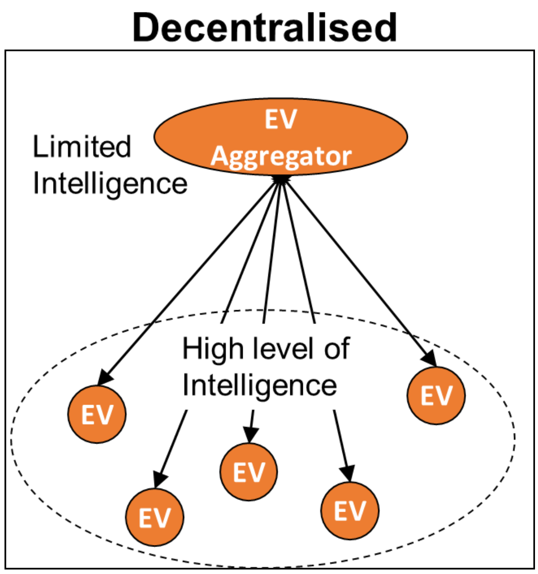

Figure 2.2: Architecture of a Decentralised Charging Control

2.4 CHARGING CONTROL STRATEGIES

The charging control strategy defines the objectives of a charging control algorithm. The main objectives aim to ensure the normal operation of a distribution network satisfying the charging requests of the EVs owners.

A popular approach for allocating EVs charging at the off-peak hours is the valley filling and peak shaving strategies. In this strategy, EVs are coordinated to charge when the load demand is low. Scheduling EVs demand to fill the overnight non-EVs demand “valley” minimises the electricity generation costs [17] and thus the cost of EVs charging.

In [18], a valley filling and peak shaving charging control strategies was followed. The EVs’ batteries were used as distributed energy storage systems to maintain the node voltage within the prescribed technical limits. This was achieved using fuzzy logic controllers to stabilise the grid. In [19] a decentralised charging control algorithm was developed, following a valley filling strategy. Each EV defines its own charging rate iteratively based on control signals broadcasted by a utility company. These signals reflect the valley level of the load demand curve. Using these signals the utility guided the EVs charging decisions. The coordination of EVs charging resulted in minimising the power losses using high uptake of EVs without network constraints violation.

In [20], a decentralised algorithm was developed to optimally schedule the EVs charging. The elasticity of electric vehicle loads was used to achieve a valley filling effect. The EVs charging scheduling strategy was formulated as an optimisation problem, aiming to flatten the demand curve. An iteratively process was used to coordinate EVs to charge according to control signals from a utility company. After each iteration, the utility was modifying dynamically the control signals based on the aggregated demand from the defined EVs charging schedules. The optimal charging profiles resulted in a valley filling effect on the non-EVs electricity demand curve.

In addition, many control strategies aim at minimising the power losses and improving the voltage profiles. A smart load management control strategy is developed in [14], for coordinating EVs charging resulting in shaving peak demand, improving voltage profile and minimising the power losses. In [21], a real-time EVs charging scheduling algorithm was developed to manage the EVs charging to minimise system losses and to keep voltage between statutory limits.

High penetration levels of RES can affect the generation mixture of each country. At those high uptakes, the distributed generators will cause voltage rises during times of low demand at the low voltage (LV) feeders. Managing the EVs charging can effectively utilise the intermittent and dispersed generation capability which is highly depended on the local weather.

In [22], a centralised smart EVs charging control algorithm for smart homes/buildings with a Photovoltaic (PV) system is presented. The optimal EVs charging schedules are determined based on the predicted PV output and electricity consumption. The EVs charging scheduling problem was formulated as an optimisation problem subject to (i) EV charging level, (ii) battery capacity, (iii) charging rate, and (iv) user preferences. The accuracy of the PV forecast model influences the performance of the model indicating the importance of a real time management of the charging of EVs. In [23], a distributed EVs charging strategy is presented, coordinating EVs charging schedules based on real-time energy market price signals. Each EV modifies the charging rate providing voltage support when necessary. This management of the EVs charging allows higher penetrations of distributed PV solar arrays, as EVs could charge when PV generation is high. In [23] V2G was not considered in the charging management scheme due to potential adverse impacts on the battery life.

Managing the charging of EV battery, requires the participation in the control scheme. However, a successful control scheme must consider the EV owner preferences trying to maximise the satisfaction of the EVs owners.

In [24] a centralised charging control algorithm was designed giving priority to the customer's satisfaction. The controller's goals are to minimise the total charging cost of customers and to maximise the revenues of the aggregator while satisfying the customer preferences regarding starting time, finishing time and desired SOC at the departure time. Constrains regarding the maximum power delivery capacity were considered to ensure the normal operation of the distribution network. Static and dynamic charging scenarios were considered. In the static charging scenario, linear programming (LP) based optimal schemes were used, considering effective heuristic algorithms for the dynamic problems. In the static scenario the customers' charging preferences are provided in advance to the aggregator and in the dynamic charging scenario, the EVs aggregator does not have knowledge when EVs may come and leave. It was demonstrated that the dynamic charging scheduling schemes provide near optimal solutions.

A decentralised EVs charging control algorithm is developed in [25], aiming to maximise the power delivered to EVs batteries subject to the technical grid constraints. Each EV defines the maximum charging rate of its own charging connection point while maintaining the voltage and cables loading within acceptable limits.

In addition, a decentralised control algorithm for EVs charging is presented in [26], aiming to maximise the levels of the user convenience. The charging coordination problem was formulated as an optimisation problem. The output of the optimisation problem defines the binary charging decisions (charged or not charged) of each individual EV. This charging control algorithm follows an on-off strategy to satisfy the EVs charging requirements while meeting circuit-level demand limits. The decentralised formulation of the charging coordination does not require the disclosure of private user state information, eliminating privacy issues which may emerge from a centralised control approach. In addition, it was stated that this decentralised control algorithm requires low-speed communication capability, addressing its suitability for a real-time application.

Finally, as the most expensive part of an EV is its battery, an interesting approach considering the battery state of health (SOH) was proposed in [27]. The four main factors that affect the battery life are temperature, SOC, charging current and depth of discharge (DOD). The battery degradation can be postponed when the battery is charged at low temperature, low SOC, low charging current and low DOD [28]. In [27] a novel decentralised EV charging control model is proposed in which a fuzzy logic controller determines the suitable charging current based on information given from the smart charger, EVs Battery Management System (BMS) and user. The capability of the control model to provide grid voltage support, extend battery life and satisfy the user's charging requirement was experimentally demonstrated through case studies.

2.5 CHARGING CONTROL TECHNIQUES

The main techniques used for the implementation of a charging control strategy include Time-of-Use (ToU) pricing policies, optimisation approaches, game theory principles, heuristic search approaches, Multi Agents Systems (MAS). Finally, additional charging control models exist utilising forecasting processes and V2G for the EVs charging management.

ToU prices are used for the management of EVs charging in [29]. ToU tariffs are financial incentives for EVs users to charge their vehicles during periods where the network is less loaded and thus the electricity rates are low. The charging coordination is formulated as an optimisation problem aiming to minimise the charging cost of EVs. The acceptable charging power of EVs battery for a specific battery SOC was considered in the charging coordination, solved by a heuristic approach designed to solve this problem. The results demonstrated the performance of the model cost, showing a reduction and flattening of the load curve.

EVs charging scheduling is by nature a multi-objective optimisation problem dealing with the trade-off between network operations and the customer's satisfaction. In [30] a EVs charging management was achieved by controlling the rate at which EVs charge. A LP technique was used to determine the optimal charging rate for each individual EV, aiming at maximising the power delivered to EVs while maintaining the normal operation of the distribution network. This control approach is maximising the utilisation of the available network delivery capacity by avoiding excessive voltage drop and systems' components overloading.

In [31]–[33] game theory principles are used to optimise the charging scheduling demand by formulating the charging problem as cooperative or non-cooperative game and trying to reach the Nash equilibrium.

A decentralised MAS management system for the charging of EVs is presented in [17]. The charging control model aims to satisfies the energy requirements of a large number of EVs based on the EVs owner's preferences and normal operating limits of the corresponding distribution network. The charging coordination problem was described as a cooperating game among EVs for achieving a valley filling on the total demand curve. The valley filling capability of EVs demonstrated that this behaviour leads to maximisation of load factor and minimisation of energy losses.

Distribution transformer and voltage constraints are considered for the charging management of a fleet of EVs [34]. The objective is to maximise a utility function in a distributed way, allocating most charging power to the EVs with the highest need for energy. The advantage of this algorithm is the low requirements for iterative exchange of messages among EVs agents, as only one message is required for charging coordination.

Heuristic approaches for the charging coordination were used in [35], [36]. A heuristic algorithm is developed in [35], to manage the EVs charging in commercial building microgrids. The charging control strategy aims to increase the utilisation of the PV energy mitigating the charging impact on the distribution network. Considering the SOC of EVs batteries and variation of PV output, the charging rate of EVs is dynamically adjusted. It was stated that the strategy is designed to operate without forecasting the PV output or EVs charging demand, resulting in lower cost of computation resources.

In [36], both centralised and decentralised control approaches were proposed. Firstly, the EVs charging management was formulated as a centralised finite-horizon optimisation problem, aiming to maximise the total utility of charging service providers. Then the initial model was decomposed into several sub-problems which can be solved iteratively, locally and in parallel using updated broadcasted control signals from the EVs aggregator. A heuristic approach was used to efficiently accelerate the convergence of the charging scheduling problem.

A smart load management strategy for the coordination of EVs charging is proposed in [37]. This strategy aims to minimise the total charging cost and the energy losses. Time-varying market energy prices defined the EVs owner priority charging time zones, while ensuring the normal operation of the distribution network (such as losses, generation limits, and voltage profile).

A noticeable category of EVs charging control models utilise forecasting processes in order to enhance their performance. EVs charging load is a specific type of demand associated with the travel patterns of the EVs owners. Their daily trips determine their energy requirements for recharging the EVs batteries as well as the times they connect and disconnect their vehicles to the charging stations. The information of where and when the EVs owners will recharge their vehicles will lead to a more effective algorithm for coordinating the EVs charging schedules. In the future smart grids there will be a bi-directional flow of information allowing the network operators to collect data of the charging events within a geographical area.

Forecasting processes as part of the EVs charging management are also included in [38] and [39]. Statistical models and Markov-processes are used to deal with the uncertainties related to the EVs travel patterns and renewable generation output. The performance of a control model is mentioned to be dependent on the accuracy of the predictions of a forecasting model used in the charging management.

In [38], a real-time centralised charging control algorithm was developed to manage the EVs charging in a grid-connected park of an industrial/commercial workplace. Diversity considering different sizes and battery capacities of EVs as well as a PV profile was applied. Probabilistic scenarios were developed using statistical models to describe the uncertainties regarding (i) the PV power, (ii) the PHEVs arrival time, and (iii) the energy available in their batteries upon their arrival. Based on these uncertainties, the charging control model manages the EVs charging aiming to reduce their overall daily charging cost, mitigating the impact of the charging park on the main grid, and contributing to shaving the peak of the load curve. This charging control model manages the aggregated EVs charging demand, considering it as a bulk of power connected to the grid. This is achieved by using a fuzzy controller for the charging management, allowing Vehicle-to-Vehicle (V2V) and V2G services between the charging park and the main alternating current (ac) grid.

In addition, a scheduling algorithm for EVs charging at a charging station with multiple charging points is developed in [39]. Renewable energy generation devices were available for the EVs charging in addition to the power from the grid. Independent Markov processes were used to model the uncertainties regarding the arrival of EVs, the intermittence of the renewable energy, and the variation of the grid power price. The objective of the control model is to minimise the mean waiting time for the charging of EVs subject to cost constraints. This is achieved by converting the EVs queue to the charging demand queue. It was proved that minimising the charging demand queue is equivalent to minimising the EVs waiting time.

Finally, charging control algorithms, where V2G and V2V power transactions functionalities are supported during the charging process, become more popular. Such algorithms are described in [40] and [41]. These functionalities were required for the intelligent workplace parking garage for PHEVs described in [40]. The components of the charging management system include a smart power charging controller, a 75-kW PV panel, a direct current (dc) distribution bus, and an ac utility grid. In this work, the future charging demand of PHEVs and the output power of the PV panels were reported as output of a forecasting model. A fuzzy logic power-flow controller was used to determine the EVs charging rates aiming at minimising the impact of the PHEVs' charging on the utility ac grid. Five different classes of PHEVs were considered based on their battery state of charge (SOC) and thus their charging needs. The fuzzy logic power-flow controller assigns different charging rates, prioritising the higher charging rates PHEVs with higher energy needs. The output of the PV forecasting model, the aggregated power demand of the PHEVs, and the electricity daily cost profile are affecting the charging rates. During the charging process, V2G and V2V power transactions are also assumed.

V2G services were also used in the charging control model described in [41]. The flexibility of EVs with V2G capability were utilised to absorb energy from wind power generators when is available, otherwise from the distribution grid. EVs charging and discharging is dynamically scheduled with the aim to minimise the charging cost subject to constraints related to satisfying the grid's normal operation and EVs charging energy requirements. This dynamic regulation of the EVs charging and discharging contributes to the stabilisation of the system's frequency and voltage.

CHAPTER 3

A DATA-DRIVEN APPROACH FOR CHARACTERISING THE CHARGING DEMAND OF ELECTRIC VEHICLES

3.1 INTRODUCTION

As the number of EVs increases, the impacts of their charging on distribution networks are being investigated using different load profiles. Due to the lack of real charging data, the majority of these load impact studies are making assumptions for the electric vehicle charging demand profiles. In this chapter a two-step modelling framework was developed to extract the useful information hidden in real EVs charging event data. Real EVs charging demand data were obtained from Plugged-in Midlands (PiM) project, one of the eight ‘Plugged-in Places’ projects supported by the UK Office for Low Emission Vehicles (OLEV). A data mining model was developed to investigate the characteristics of electric vehicle charging demand in a geographical area. A Fuzzy-Based model aggregates these characteristics and estimates the potential risk level of EVs charging demand for the corresponding distribution network. A case study with real charging and weather data from three counties in UK is presented to demonstrate the modelling framework.

EVs offer reduced transportation related emissions, reduce the energy cost of driving and in some cases eliminate the use of fossil fuels. The total electricity demand is expected to grow as the number of EVs increases [42]. The impact of EVs charging on distribution networks has been investigated in the literature. The majority of these studies use synthetic data to assess the impact of the EVs charging load due to limited access to real EVs charging data. In [43], [44] data from travel surveys are used to create EVs charging load profiles, assuming that EVs are travelling like conventional ICE vehicles.

Although EVs adoption is at an early stage, some utilities and aggregators are already collecting information from charging stations. A limited number of EVs pilots exist around the world, allowing some preliminary studies on charging demand profiles. In [45], statistical analysis of 4,933 charge events in the Victorian EVs Trial in Australia was performed. Statistical models for charge duration, daily charge frequency, energy consumed, start time of charge event, and time to next charge event were estimated to express the uncertainty of usage patterns due to different user behaviours. Data from the Western Australian Electric Vehicle Trial (2010–2012) were analysed in [46] and [47], investigating the drivers' recharging behaviours and patterns. In [48], 7,704 electric vehicle recharging event data from the SwitchEV trials in the north east of England were used to analyse the recharging patterns of 65 EVs. The results showed that minimal recharging occurred during off peak times. In [49] data from the same project were combined with LV smart meter data from Customer Led Network Revolution (CLNR) project and the impact of the combined demand profile was assessed on three different distribution networks. The results showed that the spatial and temporal diversity of EVs charging demand reduce its impact on those distribution networks. Finally, data from over 580,000 charging sessions and from 2,000 non-residential Electric Vehicle Supply Equipment's (EVSE) located in Northern California were analysed in [50]. The scope of this analysis was to investigate the potential benefits of smart charging utilising the extracted information regarding the actual trips and customer characteristics.

Monitoring the charging events will inevitably create large volumes of data. These data require effective data mining methods for their analysis in order to extract useful information. In [51]–[53] various data mining techniques were utilised to address challenges in the energy sector, such as load forecasting and profiling. In [54]–[56] data mining modelling frameworks were applied to electricity consumption data to support the characterisation of end-user demand profiles.

The rest of the chapter is organised as follows: Section 3.2 describes the real EVs charging data analysed. In Section 3.3 the proposed methodology to characterise the EVs charging demand is illustrated. A case study is presented in Section 3.4, applying the model on real EVs charging events from UK to study the charging demand characteristics, and assess their potential impact. Finally, a summary is given in Section 3.5.

3.2 DATA DESCRIPTION

EVs charging demand data were obtained from the PiM project (http://www.pluggedinmidlands.co.uk/). The PiM project, managed by Cenex, is one of the eight 'Plugged-in Places' projects supported by OLEV, the Office for Low Emission Vehicles in the UK. Two datasets were provided by Cenex, with information regarding the charging events and charging stations respectively. The charging events dataset consists of 21,918 charging events from 255 different charging stations and 587 unique EVs drivers. The charging event dataset includes information about the connection/disconnection times and the energy of each charging event for the period of 2012-2013 with event-occurrence granularity. The charging station dataset contains time-independent information regarding the location and technical specifications of all charging points (e.g. the charging power rate). The contents of the two datasets are listed in Table 3-1 and Table 3-2.

Table 3-1: Charging Event Data

Attribute Name	**Attribute Description**
Connection Time	Start time of charging event in dd/mm/yyyy hh:mm format
Disconnection Time	End time of charging event in dd/mm/yyyy hh:mm format
Energy Drawn	Energy demand of charging event in kWh
User	Unique ID for every EVs, e.g. EV1, EV2 etc.
Charging Station	Unique ID for every charging station

Table 3-2: Charging Station Data

Attribute Name	Attribute Description
Charging Station	Unique ID for every charging station
Latitude	Latitude of charging station's location
Longitude	Longitude of charging station's location
Road	The road name of charging station's location
Post Code	The post code of charging station's location
County	The county name of charging station's location
Location Category	e.g. Private Parking, Public Parking etc.
Location Subcategory	e.g. Public Car Park, Public On-street etc.
Ownership	e.g. Dealership, Hotel, Train Station
Host	Name of the charging station host
NCR	Whether or not the charging station is registered on the National Charging Registry (NCR) of UK
Manufacturer	The charging station manufacturer
Supplier	The operator of charging station
Charger Type	Power rate of charging station in kW
Connector1	Socket Pin Type e.g. 3 Pin, 5 Pin etc.
Connector2	If exists, the second Socket Pin Type
Mounting Type	e.g. Ground, Wall, Wall (tethered)

An additional dataset was acquired from the UK Met Office, with information regarding the weather in the Midlands, the geographical area under study. This dataset includes the values of various weather information (e.g. air temperature) with daily granularity for the period of 2012-2013. The weather attributes are listed in Table 3-3.

Table 3-3: Weather Data

Attribute Name	Attribute Description
Max Air Temperature	Daily maximum air temperature (˚C)
Min Air Temperature	Daily minimum air temperature (˚C)
Mean Air Temperature	Daily average air temperature (˚C)
Mean Wind Speed	Daily average wind speed (knots)
Max Gust	Daily maximum wind speed (knots)
Rainfall	Daily precipitation (mm)
Daily Global Radiation	Daily amount of solar energy falling on a horizontal surface (kJ/m^2)
Daily Sunny Hours	Daily sunshine duration (hours)

3.3 METHODOLOGY

The characterisation framework consists of three models: (i) *Data Pre-processing Model*, (ii) *Data Mining Model* and (iii) *Fuzzy Based Characterisation Model*. The *Data Pre-processing Model* provides data merging, cleaning and formatting to prepare the data for the Data Mining model. The *Data Mining Model* consists of three modules namely Clustering Module, Correlation Module and Regression Module. These modules were used to investigate the shape of the typical daily profile, the predictability with respect to weather and the trend of EVs charging demand respectively. The *Fuzzy Based Characterisation Model* aggregates the outputs of the Data Mining model into a "risk level" index of EVs charging demand in a geographical area using fuzzy logic. The characterisation framework is illustrated with Figure 3.1.

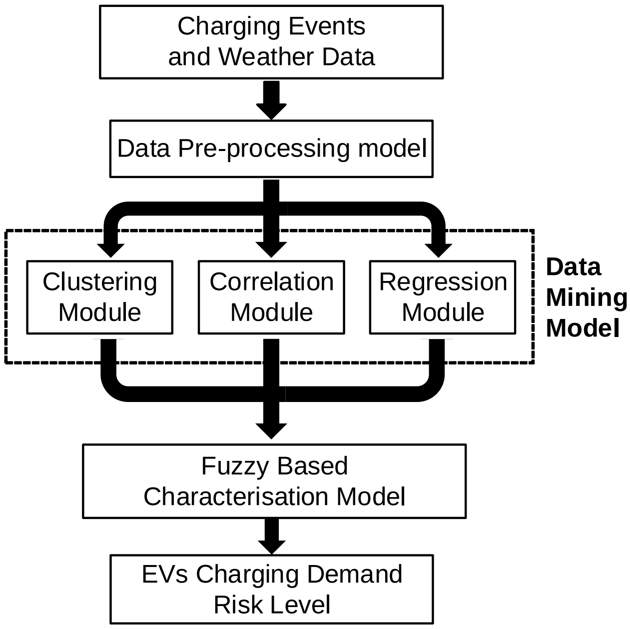

Figure 3.1: Characterisation framework

3.3.1 Data Pre-processing Model

Data of the Connection Time, Disconnection Time, Energy Drawn, Charging Station ID, Charger Type and County were selected and merged into one dataset (EV dataset). The EV dataset and the weather dataset were cleaned, removing missing and incorrect values. In the EV dataset, charging events with zero/negative energy were removed from the dataset. Charging events with average charging power higher than the nominal charger rate were corrected by calculating the actual charging duration using the nominal charger power rate. This consideration is based on the assumption that some EVs may be connected (parked) in a charging station but they are not charging. Therefore, the duration of EVs being connected to a charging station can be different to their actual charging duration. Duplicate data entries were also discovered and removed from both datasets.

Data regarding a charging event is recorded from the charging station and then forwarded to one or more data collection centres. This process involves a number of components and communication links increasing the risk of a potential failure in this chain. Corrupted or missing data are not a rare phenomenon in such complex communication networks. However, a careful analysis at this stage is also beneficial to find the location or the station’s ID from where the corrupted data are recorded, an indication of an abnormal operation.

The next stage of the Data Pre-processing is the Data Formatting stage. The EV dataset was formatted using a MATLAB script into three-time series; an hourly power time series, a daily peak power time series and a monthly energy time series. The hourly power time series was transformed into daily vectors (each of 24 values) and forwarded to the Clustering Module, whereas the monthly energy time series was forwarded to the Regression Module. All the data attributes of the Weather dataset were formatted into daily time series and merged with the daily peak power time series. The resulting (combined) time series was forwarded to the Correlation Module. The data pre-processing procedure is presented in Figure 3.2.

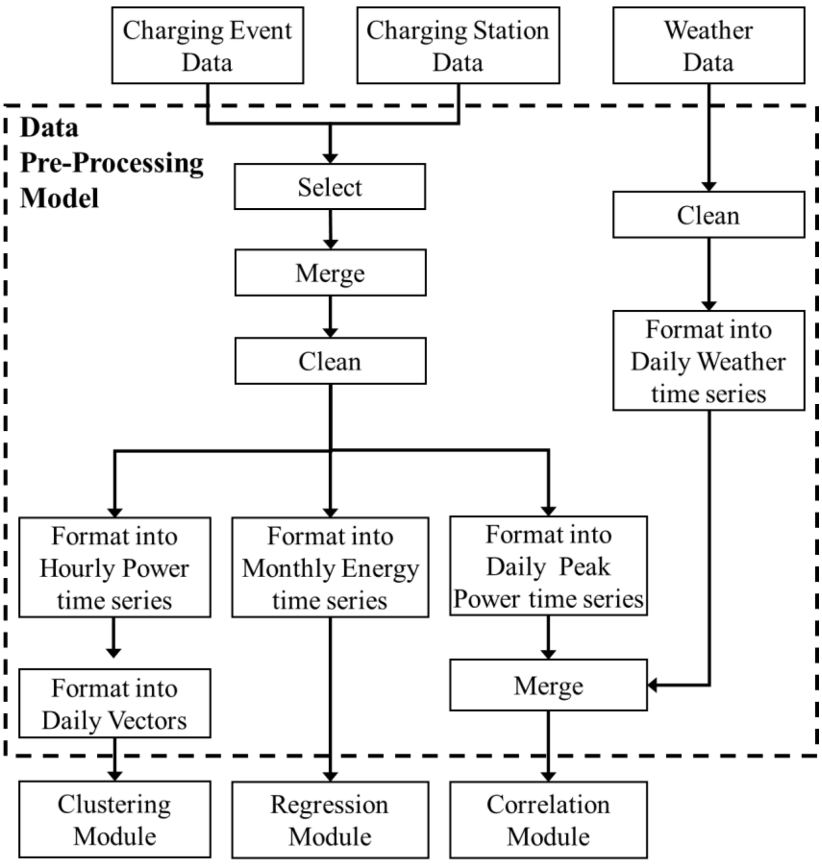

Figure 3.2: Data Pre-processing Model

3.3.2 Data Mining Model

The Data Mining Model consists of a Clustering Module, Correlation Module and Regression Module. These modules were used to investigate the shape of the typical daily EVs charging demand profile, the predictability with respect to weather and the trend of EVs charging demand respectively.

3.3.2.1 Clustering Module

The clustering module creates typical daily EVs charging demand profiles of a geographical area, based on the load demand of the corresponding charging stations. These profiles are related to the aggregated daily pattern of the EVs charging demand of a specific geographical area.

The k-means clustering method described in [57], [58], was used in this module. Initially, this algorithm selects *k* random daily vectors (Input from Data Pre-processing Model) as the initial cluster centroids and calculates the distance from each daily vector to the cluster centroids. Each daily vector is assigned to a cluster/group based on its distance with the nearest cluster centroid. Then, the new cluster centroids are obtained from the average of the daily vectors for the corresponding cluster. This process is repeated until the distances between the daily vectors and the corresponding cluster centroids are minimised. This is explained mathematically by Eq. (3.1):

$$\min_{\mathbf{c}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in c_i} \left\| \mathbf{x} - \mu_i \right\|^2 \tag{3.1}$$

where c_i is the set of daily vectors that belong to i^{th} cluster, $\boldsymbol{x}$ expresses the corresponding daily vector in c_i and μ_i is the position of the i^{th} cluster centroid.

The method requires the number *k* of clusters to be defined a priori. The Davies-Bouldin evaluation criterion was used to calculate the number *k* of clusters [59], [60]. This criterion is based on a ratio of within-cluster and between-cluster distances and is defined by Eq. (3.2):

$$DB = \frac{1}{k} \sum_{i=1}^{k} \max_{j \neq i} \left(\frac{\bar{d}_i + \bar{d}_j}{d_{ij}} \right) \tag{3.2}$$

where $\bar{d}_i$ is the average distance between each point in i^{th} cluster and the centroid of i^{th} cluster. $\bar{d}_j$ is the average distance between each point in i^{th} cluster and the centroid of j^{th} cluster. d_{ij} is the distance between the centroids of i^{th} and j^{th} clusters. The maximum value of this ratio represents the worst-case within-to-between cluster ratio for i^{th} cluster. The "best" clustering solution has the smallest Davies-Bouldin index value. Therefore, an additional step exists to evaluate the centroid selection for the dataset. A range of 1-20 clusters was considered, where 20 was found to be a reasonable maximum value [61], and the best number of clusters within this interval was calculated using an iterative process. By applying the k-means clustering method to the dataset, the k cluster centroids $\boldsymbol{c}_i$ are obtained, along with the number of vectors w_i assigned to each cluster. The followed steps of the Clustering Module are presented in Figure 3.3.

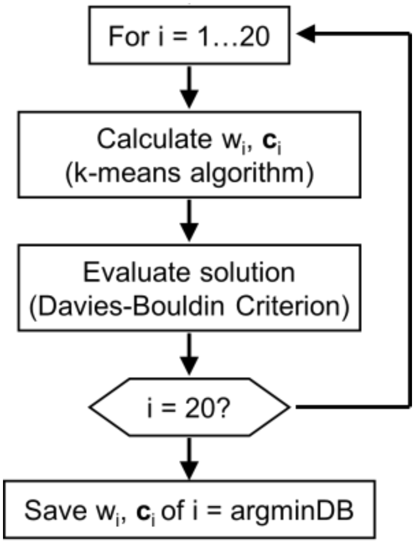

Figure 3.3: Clustering Module flowchart

The most representative cluster centroid (highest value of w_i) was used to create the typical daily EVs charging demand profile of an area. Having the daily EVs charging demand profile of an area, an index λ was defined to express the proportion of EVs charging demand during peak hours (17:00 – 20:00) [62]. The index λ was calculated using Eq. (3.3):

$$\lambda = \frac{E_{peak}}{E_{total}} \cdot 100\% \qquad (3.3)$$

where E_{peak} is the charging load during the peak hours and E_{total} is the total daily charging load. A sample of the MATLAB code used in this module is presented in Appendix A.

3.3.2.2 Correlation Module

Weather is an influential factor for the road traffic congestion and the driving behaviour of car owners [63]. In [64] the factors which affect the fuel consumption of EVs were analysed. Cold weather decreases the efficiency of the batteries performance. Additionally, heating the interior of EVs drains significantly the battery. the impact of cold ambient temperatures on running fuel use was investigated. Considering EVs on the roads, the weather will also affect their energy consumption and thus their charging demand. Identifying hidden strong relationships between weather attributes and load demand improves the forecasting accuracy of a prediction method [65].

The Pearson's Correlation Coefficient (r) was used in this module to measure the correlation between the weather attribute values and the daily peak power of EVs charging demand in a geographical area. The maximum absolute correlation coefficient value of all peak power-weather pairs identifies the most influential weather attribute.

3.3.2.3 Regression Module

The scope of this module is to investigate the monthly change of the EVs charging demand. A Growth Ratio (GR) index was defined as the ratio between the growth rate of EVs charging demand and the average monthly EVs charging demand. Linear regression analysis was applied on the EVs charging demand time series, in order to calculate the mathematical formula describing the relationship between monthly EVs charging demand (Y in kWh) and time (X in months). The formula is described with Eq. (3.4):

$$Y = \beta_0 + \beta_1 X + \varepsilon \qquad (3.4)$$

where β_0 and β_1 are the constant regression coefficients and ε is the random disturbance (error).

The slope β_1 expresses the monthly growth rate of EVs charging demand (in kWh/month). The constant regression coefficients were calculated using the Least Squares Method described in [66]. Having β_1, the GR index is calculated with Eq. (3.5).

$$GR = \frac{\beta_1}{\overline{E}_{month}} \cdot 100\% \qquad (3.5)$$

where $\overline{E}_{month}$ is the average monthly EVs charging demand.

3.3.3 *Fuzzy Based Characterisation Model*

The goal of this model was to characterise the EVs charging demand of a geographical area according to the information about the shape of the typical daily profile (λ index), the predictability with respect to weather (r) and the trend of EVs charging demand (*GR* index). To this end, a "risk level" index was defined to aggregate the potential underlying risks from these characteristics. A fuzzy-logic model was developed to capture the fuzziness of these risks and calculate the "risk level" index. Fuzzy Logic Models are useful for risk assessment purposes under such conditions [67]. The *Fuzzy Based Characterisation Model* is illustrated with Figure 3.4.

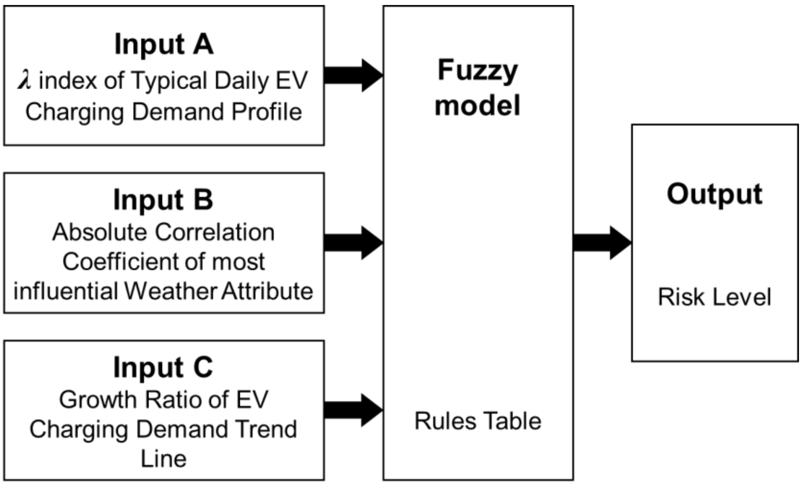

Figure 3.4: Fuzzy Based Characterisation Model

The validity of the risk characterisation model is based on the following considerations/assumptions:

i. The magnitude and duration of the peak of the typical EVs charging demand profile (captured by λ index) are underlying risk factors for the distribution network, as they affect the transformer/circuit loading and the voltage profile.

ii. The change over time of EVs charging demand (described with *GR* index) affects the long term decision regarding the planning of the network reinforcement. The aggressiveness of EVs charging demand change over time in a geographical area is also a potential risk for the network's operation.

iii. The predictability of EVs charging demand with respect to weather in a geographical area (captured by *r*), affects the accuracy of a forecasting method. Decisions taken based on a forecast are subject to the forecasting accuracy, indicating a risk for the decision maker.

iv. Analysing the EVs charging demand characteristics in a geographical area results in assessing the risks and uncertainties which will affect the mid-term normal operation of the distribution network of the corresponding geographical area.

v. As an electric power network was not used to analyse the related actual charging demand characteristics, this study quantifies only the relative risk between different geographical areas. The "risk level index" is not defined in absolute terms and thus it is used to classify relatively the level of these risks (due to EVs charging) among different geographical areas independently to their actual corresponding distribution networks.

The linguistic values used to express the input variables are Low (*L*), Medium (*M*) and High (*H*). Triangular membership functions are used to calculate the Degree-Of-Membership (DOM) for each of them, as shown in Figure 3.5 - Figure 3.7. In contrast to other kind of membership functions (e.g. Trapezoids), triangular membership functions are very sensitive to changes of the variables and thus this increase the accuracy.

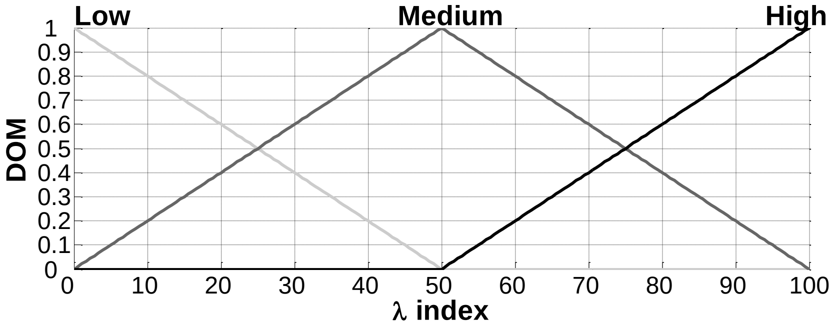

Figure 3.5: Fuzzy membership function of λ index

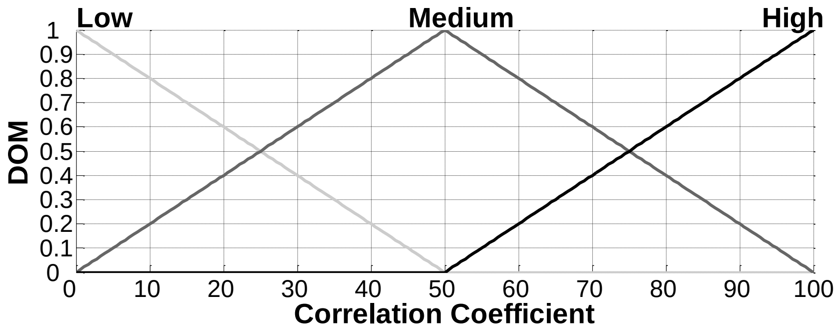

Figure 3.6: Fuzzy membership function of Correlation Coefficient

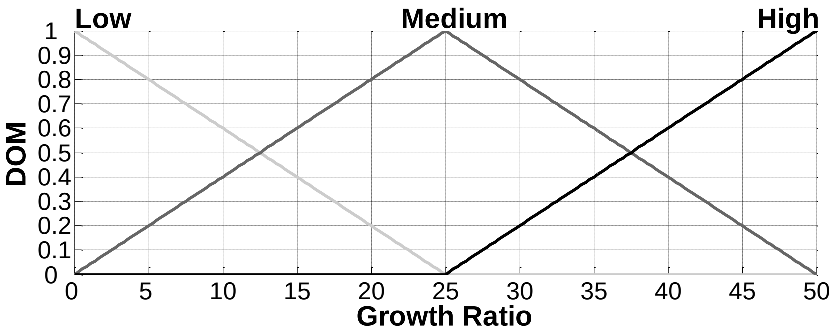

Figure 3.7: Fuzzy membership function of EVs Demand Growth Ratio

The output is fuzzified into nine fuzzy regions represented by linguistic variables; very very high (*VVH*), very high (*VH*), high (*H*), medium high (*MH*), medium (*M*), medium low (*ML*), low (*L*), very low (*VL*) and very very low (*VVL*), as shown in Figure 3.8. The rule table is given in Table 3-4.

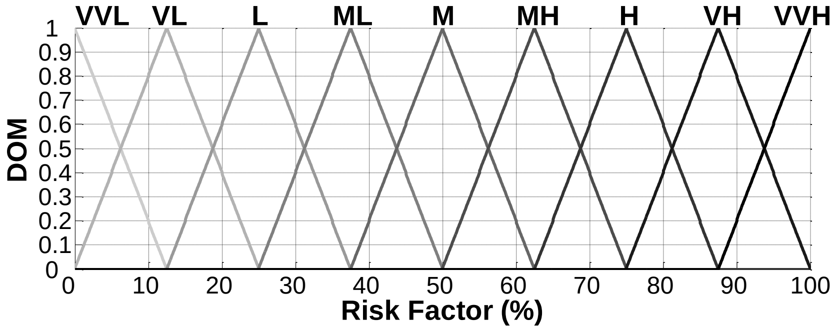

Figure 3.8: Fuzzy membership function of "Risk Level" Factor

Table 3-4: Rule Table

r	λ \ ***GR***	***L***	***M***	***H***
H	*L*	*VVL*	*VL*	*L*
	M	*VL*	*L*	*ML*
	H	*L*	*ML*	*M*
M	*L*	*L*	*ML*	*M*
	M	*ML*	*M*	*MH*
	H	*M*	*MH*	*H*
L	*L*	*M*	*MH*	*H*
	M	*MH*	*H*	*VH*
	H	*H*	*VH*	*VVH*

The design of the rule table is based on the assumption that each of the input indicators affect equally the "risk level" index. In literature, there is no research work that quantifies the level of influence of the related indicators (λ, r and GR) to the operation of an electricity distribution network. A further investigation is necessary to understand the relative impacts of these variables on the normal operation of an electricity distribution network, but this is out of the scope of this research work.

The Mamdani type inference was used (also known as the max-min inference method), which utilises the minimum function for the implication of the rules. Defuzzification was performed using the Centre of Gravity (CoG) method [68]. This method finds the centre of the area encompassed by all the rules, and thus the risk level index u is mathematically described by Eq. (3.6):

$$u = CoG = \frac{\int_{x_{\min}}^{x_{\max}} x \cdot g(x)\,dx}{\int_{x_{\min}}^{x_{\max}} g(x)\,dx} \qquad (3.6)$$

where x is the value of the "risk level" index, x_{min} and x_{max} represent the range of the "risk level" index and $g(x)$ is the degree of membership value at x.

3.4 CASE STUDY

The characterisation framework was applied on EVs charging data from three different geographical areas of the dataset. Charging events and weather data from the counties of Nottinghamshire, Leicestershire and West Midlands were analysed based on the proposed modelling framework. Figure 3.9 shows the locations of the charging stations for the corresponding geographical areas.

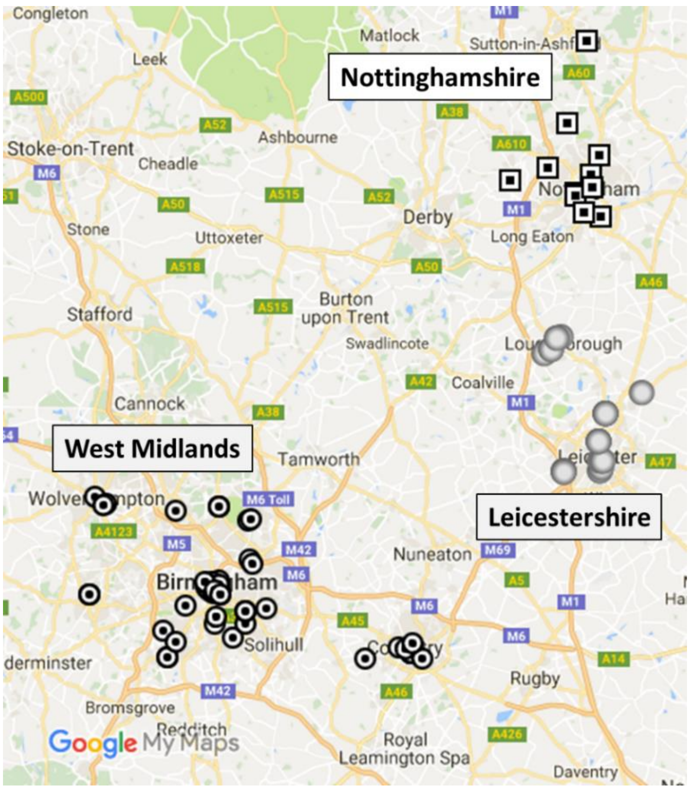

Figure 3.9: Location from the analysed charging stations

Table 3-5 shows the detailed characteristics for the analysed charging stations. For each county, information is given about the breakdown of the charging stations based on their nominal power rate and the location where they installed.

Table 3-5: Charging Station Details

County	Type of Charger	Private car park	Private parking	Private workplace parking	Public parking	Grand Total
Leicestershire	3 kw/7 kw double outlet	-	3	-	4	7
	3.7 kw double outlet	-	1	-	-	1
	3.7 kw single outlet	-	2	-	-	2
	7 kw double outlet	-	3	-	4	7
	20 kw double outlet	-	4	-	2	6
	50 kw double outlet, ac /dc	-	-	-	2	2
	50 kw single outlet, dc	-	1	-	-	1
	Total	**-**	**14**	**-**	**12**	**26**
Nottinghamshire	3 kw/7 kw double outlet	-	3	-	-	3
	3.7 kw single outlet	-	1	-	-	1
	7 kw double outlet	-	5	-	2	7
	20 kw double outlet	-	1	-	-	1
	50 kw double outlet, ac/dc	-	1	-	1	2
	50 kw single outlet, dc	-	1	1	-	2
	Total	**-**	**12**	**1**	**3**	**16**
West Midlands	3 kw/7 kw double outlet	-	1	4	-	5
	3.7 kw double outlet	-	-	-	1	1
	7 kw double outlet	2	6	1	16	25
	7 kw single outlet	-	-	1	-	1
	20 kw double outlet	-	3	-	7	1-
	43 kw/44 kw double outlet, ac/dc	-	-	-	1	1
	50 kw single outlet, dc	-	6	-	-	6
	Total	**2**	**16**	**6**	**25**	**49**
Grand Total		2	42	7	40	91

The nominal power rate of these charging stations ranges between 3kW and 50kW. When the charging stations have double outlet (two connectors), two EVs can be charged simultaneously. For higher charging power rates, dc charging is utilised while ac is used for lower charging rates.

In addition, each charging station is assigned to a location category. The analysed charging stations were installed in one of the following location categories; “Private car park”, “Private parking”, “Private workplace parking” and “Public parking”. “Private car park” and “Private parking” possibly refer to charging stations installed at private car parks or at a company’s car park which is free for its customers (e.g. supermarket, etc.). Charging stations installed in “Private workplace parking” refer to charging stations installed at a company’s car park which is free for its employees. Finally, street charging stations are assigned to the “Public parking” location category.

3.4.1 Typical EVs charging demand profiles

The *k*-means clustering algorithm was applied and the cluster centroids were obtained, along with their level of representation. Using the Davies-Bouldin criterion, the optimal number of clusters for Leicestershire was 5, for Nottinghamshire was 6 and for West Midlands was 3. The results are shown in Figure 3.10 - Figure 3.12.

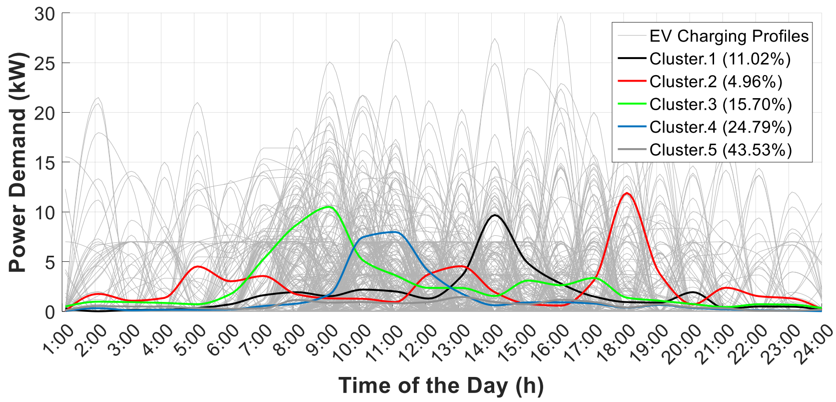

Figure 3.10: Cluster centroids for Leicestershire

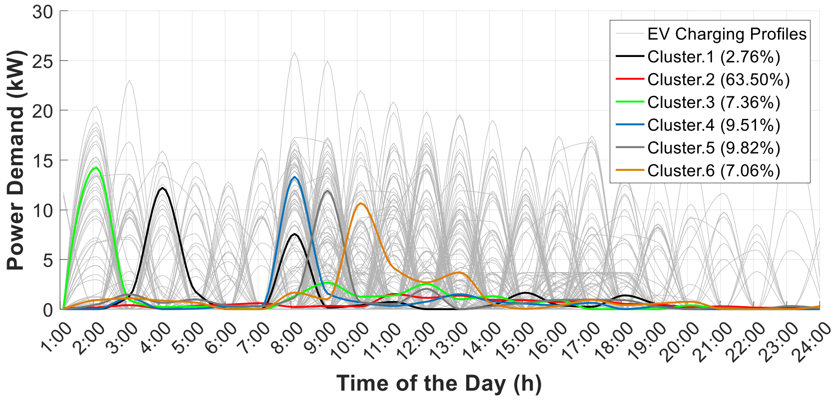

Figure 3.11: Cluster Centroids for Nottinghamshire

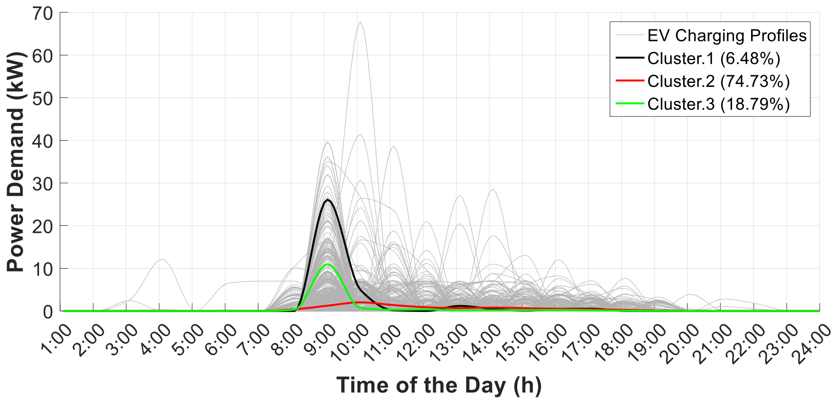

Figure 3.12: Cluster Centroids for West Midlands

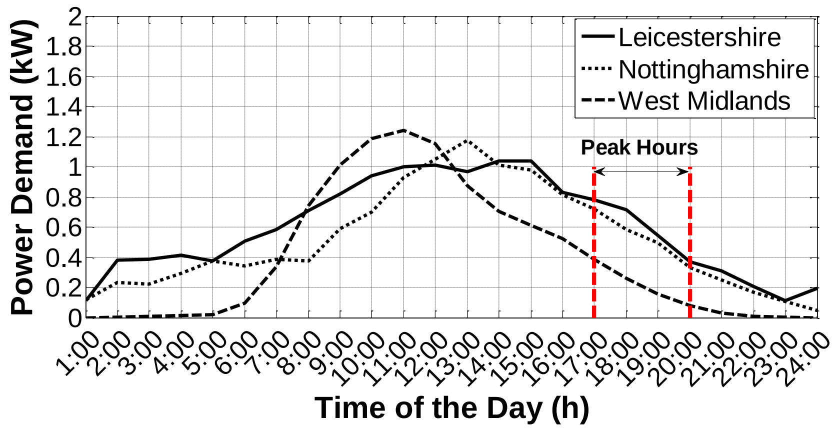

Figure 3.13: Typical Profiles for all counties

The typical daily EVs charging demand profiles for each area are presented in Figure 3.13. As seen from Figure 3.13, the three typical EVs charging profiles differ in terms of peak magnitude, timing and duration.

West Midlands shows the highest peak, however for a very short period (between 10:00 and 12:00), and no charging events during night. In this county, most of the analysed charging stations are streets charging stations.

EVs owners possibly visited the city centres during midday and used these charging stations for their charging requirements.

On the other hand, the typical EVs charging demand profiles of Nottinghamshire and Leicestershire have slightly lower peaks, but the charging activity takes place throughout the whole day. In these counties, the location of the analysed charging stations has a higher proportion of charging stations installed at private car parks. Due to the lack of additional information regarding these car parks, the charging profiles imply that EVs owners use these charging during the whole day (malls, supermarkets, etc.).

The EVs charging load during the peak hours, the total daily charging load and their ratio λ are summarised in Table 3-6. The two last columns of Table 3-6 contain information about the total number of charging events and unique EVs drivers for the corresponding geographical areas.

Table 3-6: Clustering Module Results

County	E_{peak} (kWh)	E_{total} (kWh)	λ (%)	Number of EVs	Number of Charging Events
Leicestershire	1.789	14.542	12.301	138	1944
Nottinghamshire	1.504	12.392	12.136	72	998
West Midlands	0.390	9.456	4.122	113	2013

As seen from Table 3-6, the proportion of the required energy during peak hours is relatively low for all counties. Based on Table 3-5, the location category breakdown of the charging stations indicated that the majority of the charging events are occurred mainly in commercial/public charging stations. In contrast to residential charging stations, in these type of charging stations, the EVs owner charge their vehicles for a limited period of time. Public charging stations are expected to be used for recharging when EVs owners are at their work or when they do shopping or other activities. Considering the fact that the office hours are mostly between 09:00 and 17:00, it is inferred that most EVs owners return home after their work. Thus, this can be a possible justification why the energy requirements are low during peak times.

3.4.2 *Influence of weather factors*

Table 3-7 shows the absolute correlation coefficient (*r*) values between the weather attributes and the daily peak power of EVs charging demand. The most influential factor for all areas was temperature, with the Mean Air Temperature having the highest absolute correlation indices. Leicestershire's EVs charging demand shows a medium linear correlation, whereas in Nottinghamshire and West Midlands the EVs charging demand has a weaker relationship with weather.

Table 3-7: Correlation Results

Weather Attribute	**Leicestershire (%)**	**Nottinghamshire (%)**	**West Midlands (%)**
Max Air Temperature	26.18	14.66	15.58
Min Air Temperature	26.40	14.78	17.77
Mean Air Temperature	27.06	15.24	18.78
Mean Wind Speed	22.16	10.31	7.75
Max Gust Knots	12.83	5.57	10.88
Rainfall	7.54	1.80	0.20
Daily Global Radiation	11.00	1.91	5.63
Daily Sunny Hours	16.86	1.87	6.02

As the above results show a dependency between EVs charging and Mean Air Temperature, it is useful to investigate the reasons for this relation. In a northern country like UK the climate is considered cold and thus heating the interior of an electric vehicle will result in an increase of the energy requirements.

3.4.3 *Trend of EVs charging demand*

The linear regression module described in Section 3.3.2.3 was applied on the EVs charging demand time series of the three counties to calculate its growth rate. Figure 3.14 - Figure 3.16 present the daily EVs charging demand of each county for the period 2012-2013. Noticeable gaps exist in the data, especially for Leicestershire and West Midlands. The total monthly EVs charging demand is illustrated in Figure 3.17, along with the corresponding trend line for each county. Using Eqs. (3.4) and (3.5), the regression coefficients of the trend line were calculated along with the GR index for each county. The results are summarised in Table 3-8. As seen from the results, Leicestershire shows the highest EVs charging demand growth rate. On the contrary, the EVs charging demand in West Midlands reduces slightly over the two-year period.

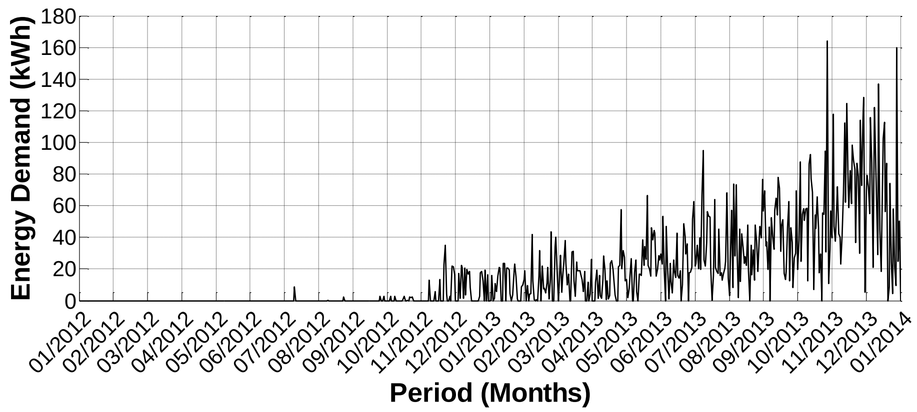

Figure 3.14: Daily EVs charging demand for Leicestershire

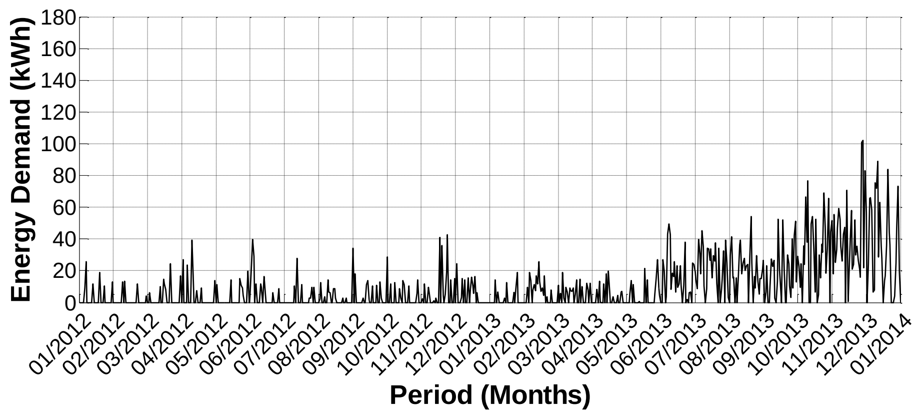

Figure 3.15: Daily EVs charging demand for Nottinghamshire

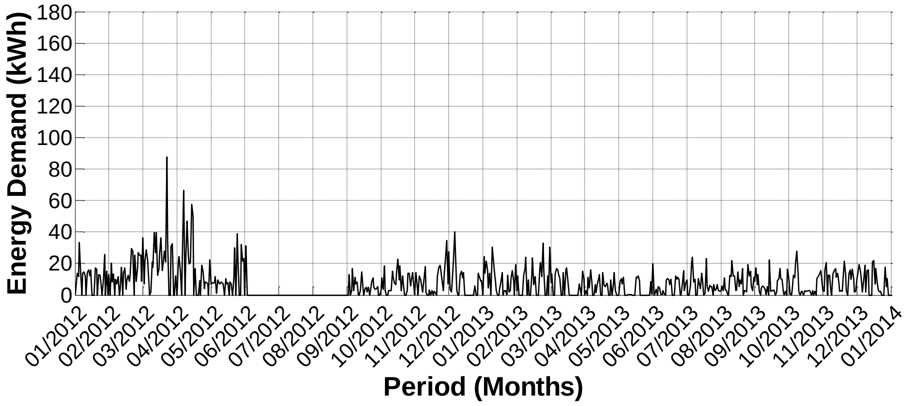

Figure 3.16: Daily EVs charging demand for West Midlands

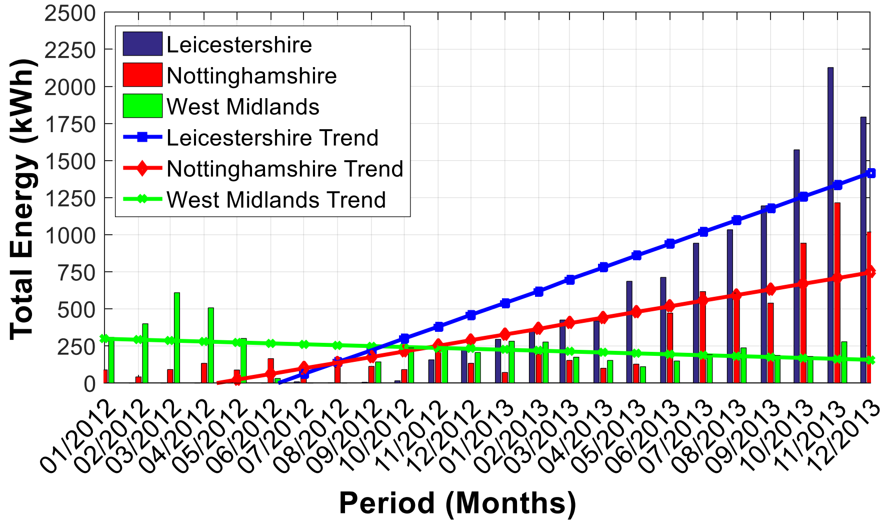

Figure 3.17: Monthly EVs charging demand trend for all counties

Table 3-8: Regression Results

County	β_1	β_0	*GR* (%)
Leicestershire	79.726	- 496.75	15.95
Nottinghamshire	38.018	- 166.94	12.33
West Midlands	- 6.149	304.69	- 2.69

As seen in Table 3-8, the trend of the EVs charging demand in West Midlands is negative, indicating that utilisation of these charging station decreases. While this occurs for West Midlands, the trend of EVs charging demand for the other two counties increases, indicating the popularity of these stations for recharging purposes. Although no additional information is given, I can assume that a potential reason may be the actual location of the charging stations. If the charging stations in West Midlands were installed at places, where are not convenient for EVs owners to visit, this may explain the decreasing trend. Therefore, for the installation of the future charging infrastructure, careful studies and plans must be carried out to ensure the optimal utilisation of the charging stations.

3.4.4 "Risk Level" Calculation

Once the Data Mining process is completed, the *Fuzzy Based Characterisation Model* uses the outputs of the *Clustering*, *Correlation* and *Regression* modules to calculate the "risk level" index of EVs charging demand for each geographical area. Table 3-9 summarises the input values for the characterisation model.

Table 3-9: Fuzzy Model Inputs

County	Input A (%)	Input B (%)	Input C (%)
Leicestershire	12.301	27.06	15.95
Nottinghamshire	12.136	15.24	12.33
West Midlands	4.122	18.78	- 2.69

Input A is the λ index of each county's typical EVs charging demand profile, as calculated from the *Clustering module*. Input B is the absolute correlation coefficient (r) value of the EVs charging demand and Mean Air Temperature (the most influential weather factor), whereas Input C is the *GR* index of the EVs charging demand (monthly basis). The latter's membership function was assumed to accept values only in the range of [0%, 50%]; negative *GR* indices were assumed as 0% increase. The outputs of the *Fuzzy Based Characterisation Model* for the three counties are presented in Table 3-10.

Table 3-10: Fuzzy Model Outputs

County	Risk index (%)
Leicestershire	34.1
Nottinghamshire	34.8
West Midlands	23.5

As seen from Table 3-10, the EVs charging demand in West Midlands has the lowest value for “risk level” index. Looking at the corresponding input values, such a result is expected as the EVs charging demand has a descending trend (*GR* index) and low energy requirements during peak hours (λ index). Leicestershire and Nottinghamshire on the other hand are characterised with higher values of the risk level index by the model. Similar output values for these areas are not unexpected as Leicestershire has slightly higher growth ratio and energy requirements, however the EVs charging demand in Nottinghamshire is more unpredictable (lower correlation coefficient).

3.5 SUMMARY

A characterisation framework for EVs charging demand was developed. This framework utilises data analysis methods to extract information hidden behind charging events in order to identify the characteristics of the EVs charging load. This information was then used by a fuzzy based characterisation algorithm to estimate the underlying relative risks for the distribution networks among different geographical areas independently to their actual corresponding distribution networks. The framework was applied on a dataset of real charging events from three counties in UK and their “risk level” index was calculated.

The risk level index gives a spatial indication of the potential impact of the EVs charging demand on a distribution network in the nearby (mid-term) future. Areas with high “risk level” factor are candidates for further investigation. However, the interpretation of this index is highly influenced by the network characteristics. Other operational metrics (e.g. maximum load capacity) of the corresponding network should also be considered to plan possible network reinforcements. Charging strategies or other DSM applications can be designed for an area based on its specific EVs charging load characteristics. For example, areas where the EVs charging demand is high during peak times, a valley filling strategy might be useful, whereas areas with random EVs charging events might need to invest on a different DSM solution.

CHAPTER 4

FORECASTING MODELS FOR THE EVS AGGREGATOR

4.1 INTRODUCTION

As mentioned in Section 2.2, the EVs aggregator represents an energy market entity which can manage the EVs charging demand directly or indirectly. In some cases, the EVs aggregator can also manage small scale renewable energy generation in a geographical area utilising the flexibility from EVs to consume this generation locally.

However, EV aggregators have to deal with various uncertainties which affect the performance of the EVs charging management. These uncertainties are associated with the random charging patterns of individual EVs owners and the volatility in the energy market prices. The energy market prices volatilities are caused by large penetrations of variable RES and random load demand. In particular, uncertainties on power generation increases with higher share of intermittent RES in the generation mix such as wind power.

These uncertainties could pose technical and financial risks to EV aggregators' operation. Therefore, the EVs aggregators must develop the appropriate methods to forecast the future EVs charging demand as well as the available renewable generation in order to effectively coordinate EVs charging.

The rest of the chapter is organised as follows: Section 4.2 describes the development of a generic framework for the EVs load forecast methodology based on the data mining principles. Also, two case studies based on real charging event data are presented. In Section 4.3, a stochastic renewable energy generation forecasting model is described. The performance of this model is evaluated using real wind power data. Finally, a summary is given in Section 4.4.

4.2 A FORECASTING MODEL FOR EVS CHARGING DEMAND

As the penetration of EVs grows, the number of recharging stations where EVs can replenish their energy needs is increasing. These charging stations are divided in three main categories based on their location and technical specifications: private residential, private non-residential and public charging stations [69]. The private residential charging stations are installed mainly at home and have a slow charging rate. Private non-residential chargers are usually installed in the parking lot of a company, accommodating the EVs energy needs of its employees. Local authorities install publicly available recharging infrastructure on the streets, mainly located at the city centres. The majority of the charging stations have data collection capabilities, keeping records of the EVs charging events.

With the number of EVs and charging stations gradually rising, charging events are going to occur in various locations and times. This creates a large volume of data, recorded and stored by the individual charging stations or back up offices [70]. Collecting and managing the dispersed data in a central point is impractical [71]. Therefore, distributed data collection centres are proposed to manage the data from a group of charging stations. The main role of these centres is to aggregate the data from many charging stations offering data reduction services.

The databases contain information related to the time and place of each charging event, the amount of requested energy and in some cases the ID of the EVs and/or the charging station. This information is used for understanding the charging and travel patterns of the EVs owners, as well as the activity of each charging station.

The value of the collected data is useful in many different fields. Various actors can use this information according to their targets. For example, a Distribution System Operator (DSO) uses the temporal and spatial information of the charging events to plan future investments in network upgrades. In addition, these data can also be used to determine the EVs charging load profiles [72]. The flexibility of EVs charging load will allow new market entities like EVs aggregators to develop the suitable business models for DSM in order to provide ancillary services to grid operators [73], [74]. EVs are entities that are part of both electricity and transport networks. Charging EVs in public or street locations requires at least a parking space per charging point. Due to the finite number of parking spaces in a city, especially in the city centre, the number of EVs that are charging at the same time is limited. This will affect the road transport networks particularly the daily travel patterns and the congestion parameters [75]. Authorities should take into consideration this effect and utilise proper mechanisms and parking schemes for the EVs deployment.

Different data collected from a typical charging event are used for different applications. More specifically, the analysis of real charging data assists in creating typical EVs charging profiles, information which is important to the planning of the future EVs charging infrastructure. The appropriate number and the charging rate of the public charging stations of an area are defined by understanding the trend of the charging data. Moreover, the extracted charging load patterns are used to explore opportunities for possible ancillary services to the grid operators (load management, frequency response). Using these real data is also important to develop appropriate business models to promote the mass deployment of EVs. Finally, EVs charging is not only affecting the electric power systems but also the transport networks. For this reason, authorities are considering possible impacts of EVs charging on the traffic condition or parking spaces of a geographic area.

Due to the variety of charging data, a generic data analysis methodology is needed for extracting the relevant information for each application. The complexity of this process and the large amount of data, make data mining techniques a promising solution in extracting information from charging events records [51], [52]. Particularly, EVs load forecasting is influenced by fluctuating factors like driving and travel patterns of each EV owner. These patterns are important to be considered in order to estimate the charging demand. Therefore, the stochastic nature of the EVs charging demand factors forces the use of advanced forecasting techniques which are able to decipher all the patterns. The use of artificial intelligence techniques enables the decoding of complicated historical charging events despite the high randomness they appear. The scope of this research work is to evaluate the performance of various data mining methods in forecasting the charging demand of an EV fleet. For this evaluation, two different case studies were considered based on real EVs charging data.

4.2.1 Data Mining Methods

Data mining is an interdisciplinary process combining different techniques like machine learning, pattern recognition and statistics in order to extract information from large datasets [53]. It is the process of discovering hidden patterns, associations, anomalies and significant structures in large amounts of data. Data mining is a step in the procedure known as Knowledge-Discovery-from-Databases (KDD) [76]. Data pre-processing, data formatting and data mining actions constitute the KDD process, as presented in Figure 4.1.

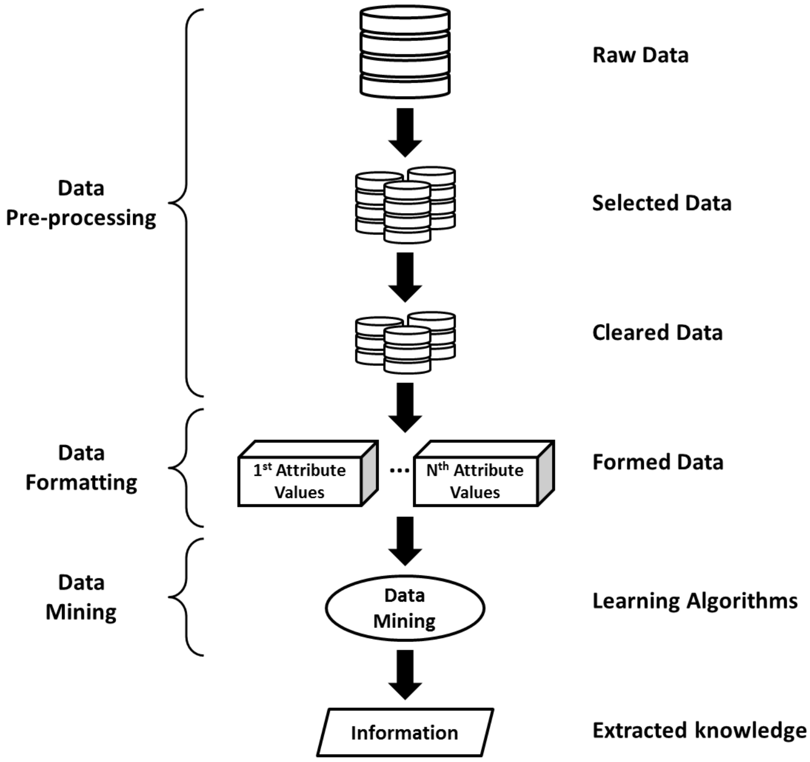

Figure 4.1: The flowchart of the KDD process

The Data Pre-processing stage includes data selection and data clearance actions. Once the data are collected from a database, a preliminary analysis takes place in order to understand and select the useful data. This selection is critical for the extraction of information as the unnecessary data create noise and lead to incorrect conclusions. Furthermore, the data selection reduces the size of the dataset, resulting in lower storage and computational requirements, as well as in reduced processing time. The selected data are then forwarded into a sequence of clearing actions, where missing values are either removed or forecasted whenever it is possible. In addition, outliers like unrealistic charging durations are detected and eliminated so that the extracted conclusions are not distorted.

In the Data Formatting stage, data are transformed and formatted based on the data mining technique of the next stage. Attributes are defined to express the different features in the dataset. The data are then organised in attribute groups that express the same type of information. This arrangement is essential for the KDD procedure and a potential error in the Data Formatting stage will influence the outcome.

The Data Mining stage is the final and the most important stage of the KDD procedure. This stage includes data processing with one or more algorithms, defined in agreement with the goal of the analysis. Two main types of algorithms exist based on the applied learning procedure: unsupervised and supervised learning algorithms. Unsupervised learning algorithms include clustering procedures, often useful for an initial understanding of a dataset, as well as (depending on the application) data partitioning and pattern recognition. In supervised learning algorithms each data string is a pair of an attribute vector and a target (desired) value. Because of this formulation the algorithm is forced to learn the correlation between the attributes and the target values and they are widely used for classification and forecasting tasks. In order to evaluate the learning capability of a data mining method, the initial dataset is divided in the training and the testing dataset. The training dataset is provided to the KDD procedure to learn the correlations among the attributes and create a trained model. This process is called “training process”. The testing dataset is then forwarded to the trained model to evaluate its performance (“testing process”). In case the trained model fails to provide the desired output (within a confidence interval), a reconfiguration of the data mining method is applied and the training-testing sequence is repeated. This iterative process is terminated once the desired output is reached.

In this research work four data mining methods were considered and briefly described in the following subsections.

4.2.1.1 Decision Tables

Decision Table algorithms build and use a simple decision table majority classifier as proposed by Kohavi [77]. The dataset is summarised with a decision table which contains the same number of attributes as the original dataset. The simplicity of creating and reading a decision table is one of the method’s main advantages. The main structure of a decision table is shown in Table 4-1.

Table 4-1: General structure of a Decision Table [18]

	Decision Rule 1	Decision Rule 2	Decision Rule 3
Conditions	Condition Entries	Condition Entries	Condition Entries
Actions	Action Entries	Action Entries	Action Entries

In general, a decision table is divided into four quadrants. The upper two quadrants contain the conditions for each Decision rule. The lower two quadrants describe all the possible actions for every corresponding condition. However, one important drawback is that in complex datasets with many attributes Decision tables may became extremely large.

4.2.1.2 Decision Trees

Decision Trees are a supervised learning method used for classification tasks. Decision Trees are used to classify instances by categorising them taking into account the feature values. All the middle nodes represent an evaluation of a condition (Decision Nodes) and the terminal nodes (Leaf Nodes) represent the decision result. A typical structure of a decision tree is shown in Table 4-2.

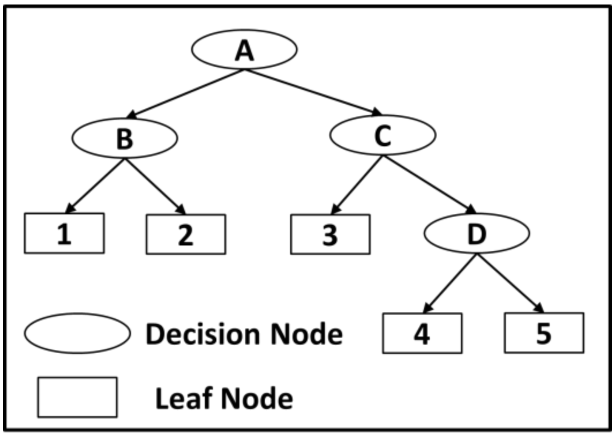

Figure 4.2: Typical structure of a decision tree

In this research work the Reduced Error Pruning (REP) Tree was used. REP Tree algorithm is a fast decision tree learner [78]. It builds a decision tree using known information and prunes it using reduced-error pruning. With this algorithm the possibility of pruning sub-trees is examined and evaluated according to the reduction or not of the error. In case of an error reduction, the sub-tree is pruned and the final tree is smaller and more accurate.

4.2.1.3 Artificial Neural Networks

Artificial Neural Networks (ANNs) were inspired from the human neurons. ANNs are able to find hidden correlations between input data and target value and solve complicated problems despite noise and fluctuation in the data. There are various types of ANNs and the most known are the Multi-Layered Perceptron (MLP), Radial Basis Function (RBF) and the Kohonen networks [79]. In this research MLP was selected to provide forecasts. MLP consist of three basic layers: The Input Layer, the Hidden Layer and the Output Layer [76]. The Input layer can have any number of inputs. The Hidden Layer can contain one or more (sub) layers and each of them can contain one or more nodes. They are called "Hidden" because they receive internal inputs and produce internal outputs, not directly connected to the external layers. The only existing connections are between the input layer and first hidden layer and the last hidden layer and the output layer. The structure of an MLP neural network is described in Figure 4.3Table 4-3.

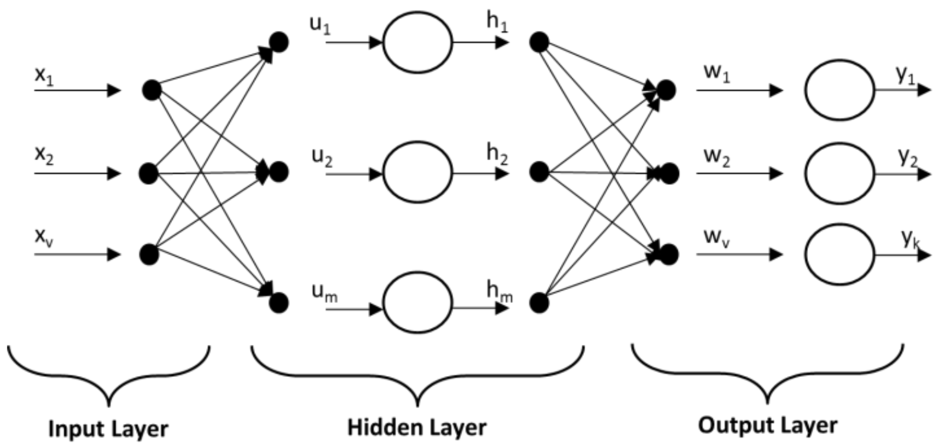

Figure 4.3: Structure of an MLP neural network

4.2.1.4 Support Vector Machines

Support Vector Machines (SVM) is a machine learning method associated with classification, regression and other learning tasks and was developed by Vapnic, Guyon and Boser [80]. SVM tries to find linear separations between the data ("decision boundaries" for separating one class from another). Assuming data with two attributes, SVM depicts them into a two dimensional space and search for possible separating lines. If the data are depended on three attributes, they are projected on a three dimensional space and SVM searches for the possible separating planes. Generalising for n-attributes, the depiction is on an n-dimension space and SVM search for separating hyperplanes. SVM will find many different lines or hyperplanes which divide the data. The optimal line/hyperplane is selected based on the maximisation of the separating distance. When SVM cannot find linear separations in the initial data, they transform these data into new spaces using the kernel functions. For each kernel type, there are different variables that need to be tuned in order to perform effectively [81]–[83]. The Gaussian RBF described in Eq. (4.1) is found to outperform in many cases of learning tasks and thus this kernel type was used in the EVs load forecast algorithm [84]. Thus, for the EVs load forecast method the parameters γ, C and ε are considered in the tuning process. Parameter γ expresses the width in the kernel function [83], parameter C represents the trade-off between the training error and the maximum number of data points that can be separated in all possible ways [85], while parameter ε influences the number of support vectors and consequently the generalisation capability of the model [86].

$$K(x,y) = \exp\left(-\gamma\left(\|x-y\|\right)^2\right),\ \gamma > 0 \qquad (4.1)$$

where x and y express samples of different attribute vectors. An example of a simple two-dimensional case is illustrated in Figure 4.4.

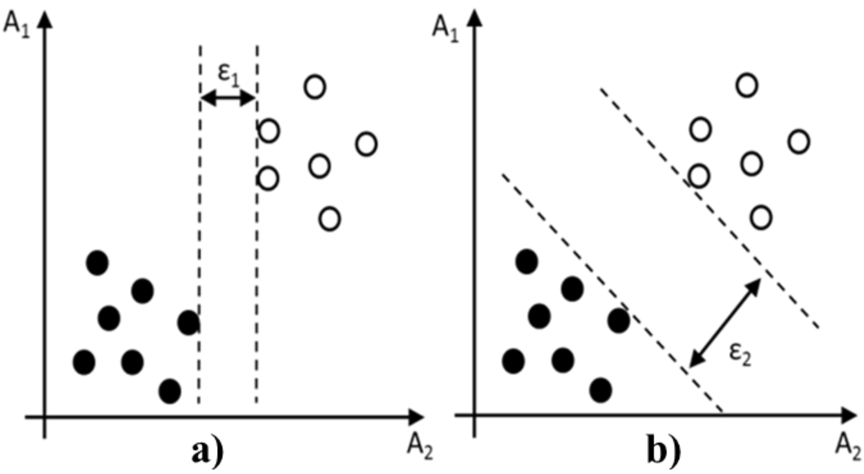

Figure 4.4: a) A random pair of separating lines, b) The pair of separating lines with the maximum distance

4.2.2 Data Pre-processing stage

In order to develop the EVs load forecasting algorithm, all the stages of the KDD process are considered. Recorded datasets of EVs charging events contain both useful and irrelevant information to the purpose of the particular analysis. For example, in case the purpose is a behavioural analysis of the EVs owners, information regarding the time, the location and the User ID of each charging event are most relevant in contrast to data regarding the charging station manufacturer. On the other hand, in case the purpose is to calculate the utility of a particular company's charging stations, information about the charging station manufacturer becomes more important than data regarding the User ID. Therefore, according to the target of the particular analysis and the availability of the data, an appropriate data selection process is important to be applied. Data regarding a charging event is recorded from the charging station and then forwarded to one or more data collection centres. This process involves a number of components and communication links increasing the risk of a potential failure in this chain. Corrupted or missing data are not a rare phenomenon in such complex communication networks. Therefore, data clearing processes are important to remove the noisy data and the outliers. For example, charging events with zero or negative energy are removed from the dataset. However, a careful analysis at this stage is beneficial from another point of view. By keeping track of the location or the station's ID from where the corrupted data come, an indication of the normal/abnormal operation is obtained.

Due to the amount of charging events and variety of additional data, the Data Pre-processing stage of the KDD process is time consuming without an automated way of processing this volume of information. Furthermore, it is highly possible that additional information about charging events (Stations info or User Info) may be stored in different files. Thus, in order to effectively cope with the data, a script for integrating all sources of information in one dataset is developed. Then, another script is executed in order to select the appropriate data for the ongoing analysis as well as to check the data for mistaken values or outliers within the dataset. The steps of the Data Pre-processing stage are illustrated in Figure 4.5.

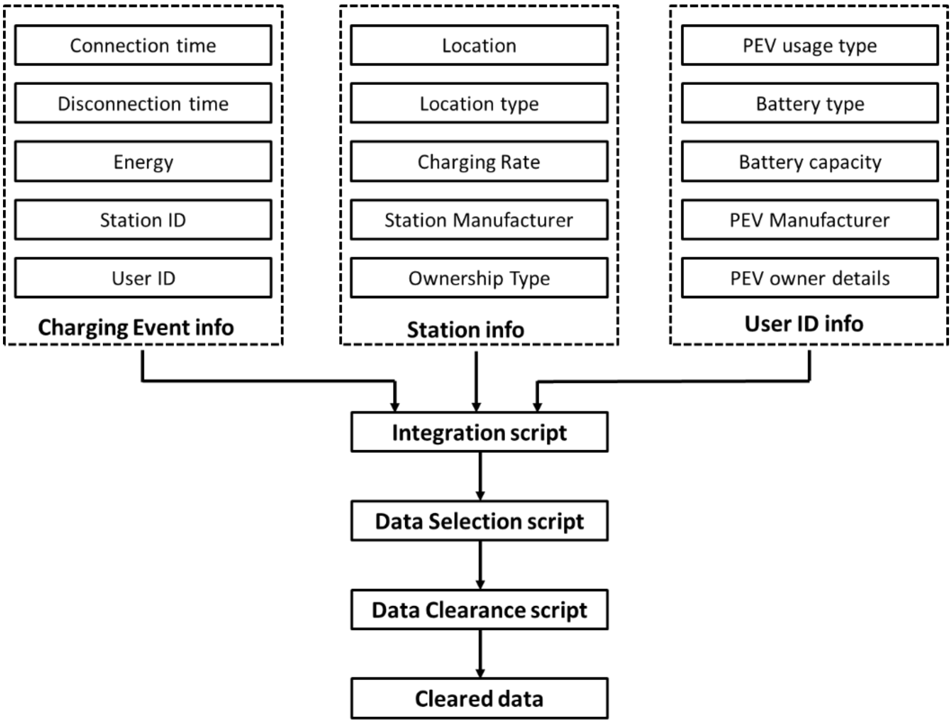

Figure 4.5: The Data Pre-processing stage

4.2.3 Data Formatting stage

In the Data Formatting stage, a transformation script is applied to the Cleared Data in order to change their structure. For forecasting applications, the structure of the data follows the template presented in Table 4-2.

Table 4-2: Structure of the Formed Data

Target Title	**Attribute_1 Title**	**…**	**Attribute_M Title**
Target Value-1	Attribute_1 Value-1	…	Attribute_M Value-1
Target Value-2	Attribute_1 Value-2	…	Attribute_M Value-2
…	…	…	…
Target Value-N	Attribute_1 Value-N	…	Attribute_M Value-N

This structure is important for training the model to decode the correlations among the attributes. The time horizon of the forecast defines the time difference between the target and the attribute values. For a day ahead EVs charging demand forecast for example, the target values are related to the charging demand of *N* day while the attribute values refer to *N-1* day. Moreover, the resolution of the forecast defines the time difference between consecutive rows. In the day ahead EVs charging demand forecasting case for instance, assuming a half hour resolution, each row is related to a specific half hour of a day. The new data structure is presented in Table 4-3.

Table 4-3: Data structure for a day-ahead EVs charging demand forecast with a half hourly resolution

EVs charging demand	**Attribute_1 Title**	**…**	**Attribute_M Title**
EVs charging demand for 1st half hour of N day	Attribute_1 Value for 1st half hour of *N-1* day	…	Attribute_M Value for 1st half hour of *N-1* day
EVs charging demand for 2nd half hour of N day	Attribute_1 Value for 2nd half hour of *N-1* day	…	Attribute_M Value for 2nd half hour of *N-1* day
…	…	…	…
EVs charging demand for 48th half hour of N day	Attribute_1 Value for 48th half hour of *N-1* day	…	Attribute_M Value for 48th half hour of *N-1* day

4.2.4 The Training and Forecasting Process

Once the Data Formatting stage is complete, the formed data are used to train the forecasting model. The training process of the forecasting model is shown in Figure 4.6.

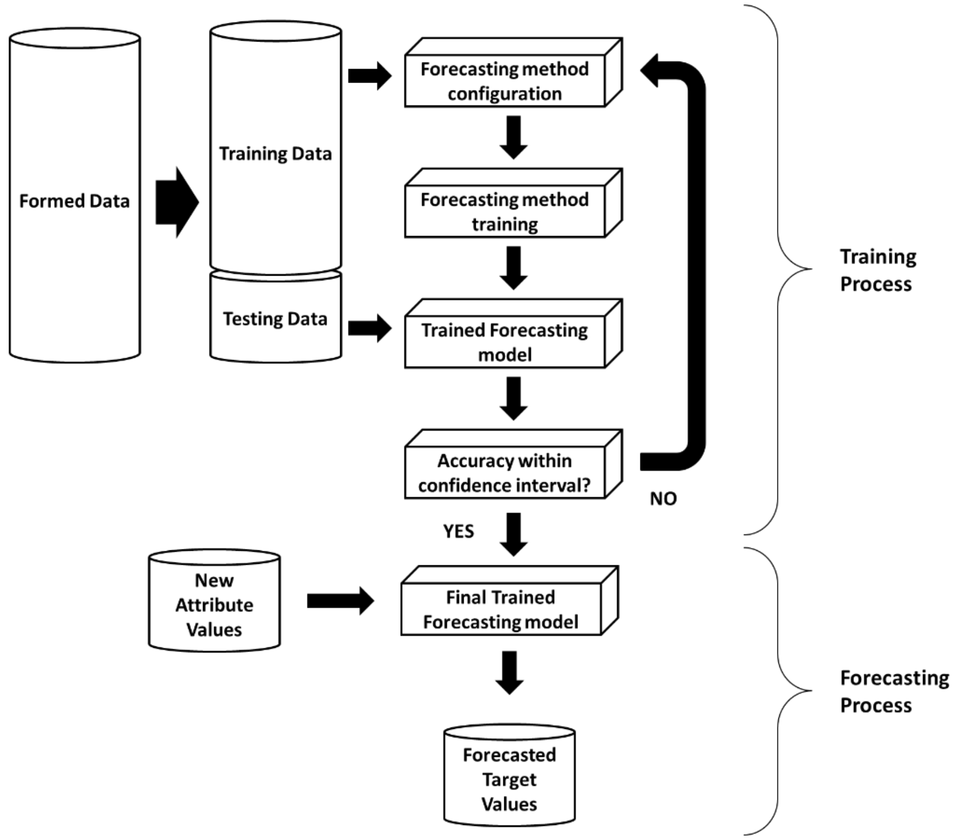

Figure 4.6: The Training and Forecasting Process

An appropriate data mining technique is selected for the forecasting model depending on the characteristics of the EVs charging events. Factors like randomness can make one data mining technique more suitable than another. For example, advanced data mining techniques are needed for an accurate forecast, if high fluctuating data are coming from a public charging station. On the other hand, charging events from a residential charging point are more periodic and easier to predict. A simple method like linear regression can be used for less complicated forecasting models while powerful methods like SVM, ANNs and Trees [87], [88] are used by advanced forecasting models. Regardless the fluctuation of data, a proper configuration of the selected data mining method is also important for the accuracy of the forecasting model (parameters tuning process).

The formed data are separated in two parts, the Training and Testing dataset. Since the appropriate data mining method and its parameters are selected, the model is trained based on the training dataset. Once the model is trained, the testing dataset is used to evaluate the performance of the forecasting model. In the evaluation process, only the attribute values of the testing dataset are supplied to the trained model in order to forecast the corresponding target values of the testing dataset. By comparing the forecasted values with the actual target values of the testing dataset, the performance of the model is evaluated. If the accuracy of the model is not sufficient, a reconfiguration of the parameters of the data mining method is required and then the model is retrained. Subsequently, the performance of the new trained model is evaluated and this iterative process terminates when the accuracy level is reached. In this research work the termination criterion used for training the model was a Mean Absolute Percentage Error (MAPE) with less than 5%.

Once this procedure is completed, the forecasting model can be used on unknown data. The new dataset includes values in the attribute columns, while the target values are missing (unknown). The forecasting model based on the correlations learned from the training process and the supplied attribute values will predict the unknown target values. Note that the time difference between the attribute and target values of the new dataset will match the one of the training dataset. If the model was trained for a day-ahead forecast for example, this will be the time horizon of the forecast and the target values of the next day constitute the output. A sample of the MATLAB code used for the training and testing process of the EV load forecasting model is presented in Appendix B.

4.2.5 Performance Indices

The accuracy of the model output was assessed using MAPE, Root Mean Square Error (RMSE) and r-Correlation. The training and testing duration were also considered to evaluate the performance.

MAPE is an accepted industry standard for measuring the accuracy of a forecasting method while RMSE penalises large absolute differences between actual and forecasted values. The r-correlation shows the general performance of a model. These performance indices are calculated using Eqs. (4.2) - (4.4).

$$MAPE = \frac{\sum_{i=1}^{N}\left(\frac{|X_i - Y_i|}{X_i}\right)}{N} \times 100\% \tag{4.2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{N}} \tag{4.3}$$

$$r = \frac{\sum_{i=1}^{N}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{N}\left(X_i - \overline{X}\right)^2}\sqrt{\sum_{i=1}^{N}\left(Y_i - \overline{Y}\right)^2}} \tag{4.4}$$

where N is the number of the forecasted values, X is the actual values, Y is the forecasted values, $\overline{X}$ is the mean of the actual values and $\overline{Y}$ is the mean of the forecasted values.

4.2.6 Case Studies

The data mining tasks were conducted on an Intel i3 Processor Platform, which consists of 3GB RAM and Microsoft Windows 7 operating system. WEKA 3.6.9 software tool was used [89]. WEKA is a widely known toolkit for machine learning and data mining algorithms such as regression, classification, clustering, association rules, visualisation and data processing, developed by the University of Waikato. Data sets used in WEKA was in Comma-Separated Values (CSV) file format, where values are separated by commas and sorted according to the attribute.

4.2.6.1 Case Study 1: Residential charging Stations in USA

The EV Project is a large deployment of EVs and charging infrastructure in United States of America (USA) launched by ECOtality on October 1, 2009 [90]. With grants received from the Department of Energy and the support of various Industrial Partners, EVSE was installed in major cities and metropolitan areas across the United States. By the end of 2012, 7,376 EVs (Nissan Leafs, Chevrolet Volts and Smart4Two) participated in the project [90]. A total number of 9,333 charging stations were installed, 6,694 of which are residential, 2,583 commercial and 56 dc fast chargers. For this case study, aggregated residential data from the 4th Quarter of 2012 were provided by ECOtality, in order to test the performance of various data mining methods.

4.2.6.1.1 Data Description

Data from ECOtality project include distribution curves that were used to create a representative EV fleet and its charging demand for one year. Figure 4.7 and Figure 4.8 show the distribution of the energy consumption and the duration per charging event.

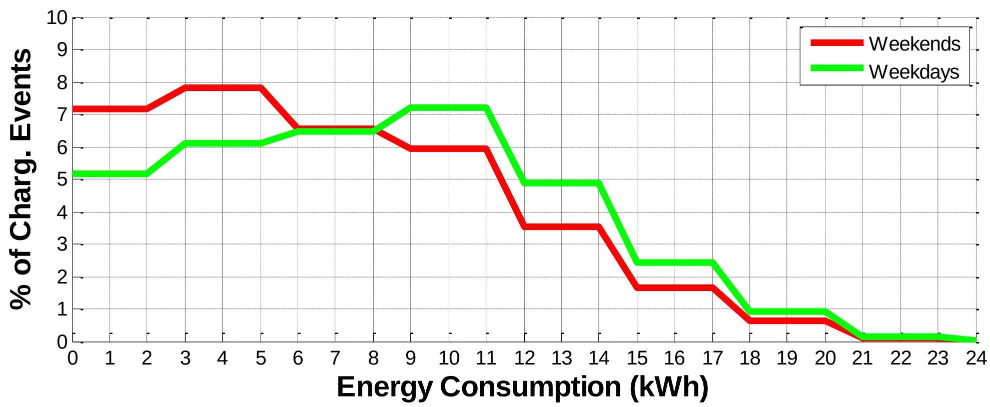

Figure 4.7: Energy consumption distribution / charging event

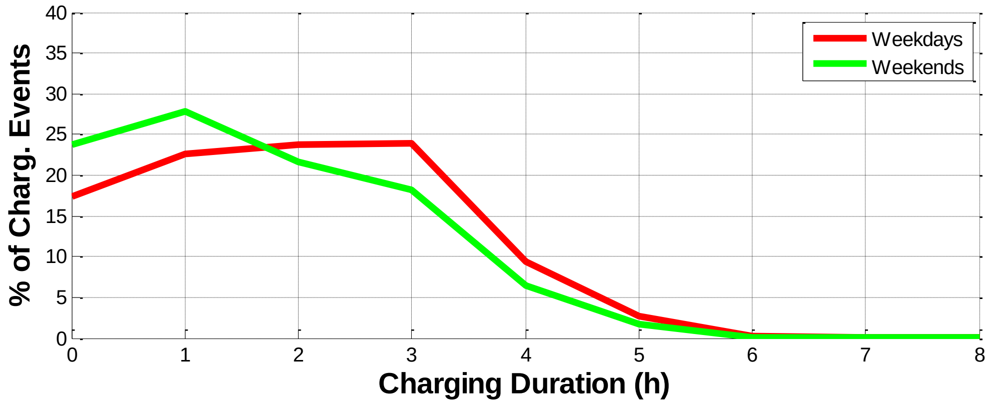

Figure 4.8: Charging duration distribution / charging event

A fleet of 3000 EVs was considered and their charging events were created based on the above distributions. Arrival times for the EVs were estimated using the Charging Availability graph for a typical weekday/weekend as shown in Figure 4.9.

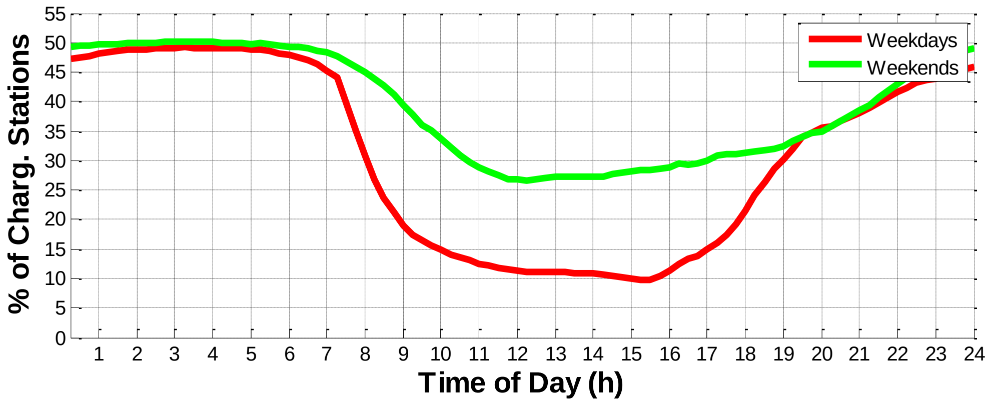

Figure 4.9: Charging Availability for 24 hours

Using the above data, the aggregated charging demand was created for one year on a half-hourly basis. The attributes for each half hour are shown in Table 4-4.

Table 4-4: Attribute used for the training process

Attribute Name	Description
Previous Day Load	The charging demand of the same day of previous week for each half hour
Week	Number of the week (1-53)
Day	Number of the day (1-7) starting with Monday
Type of Day	Weekday or Weekend.
Half Hour	1-48 half hour parts of each day
Number of New Connections	The new EV plug-in connections for every half hour
Total Charging Connections	The number of EV that are connected and charging for every half hour

Once the dataset is structured using the above template, the last day of the dataset was selected for the Test Dataset. All the previous ones are the Train Dataset.

4.2.6.1.2 Results

Using the procedure described in Figure 4.6, the forecasts of the four data mining methods are shown in Figure 4.10 in comparison with the actual demand. The performance measures for each method are summarised in Table 4-5.

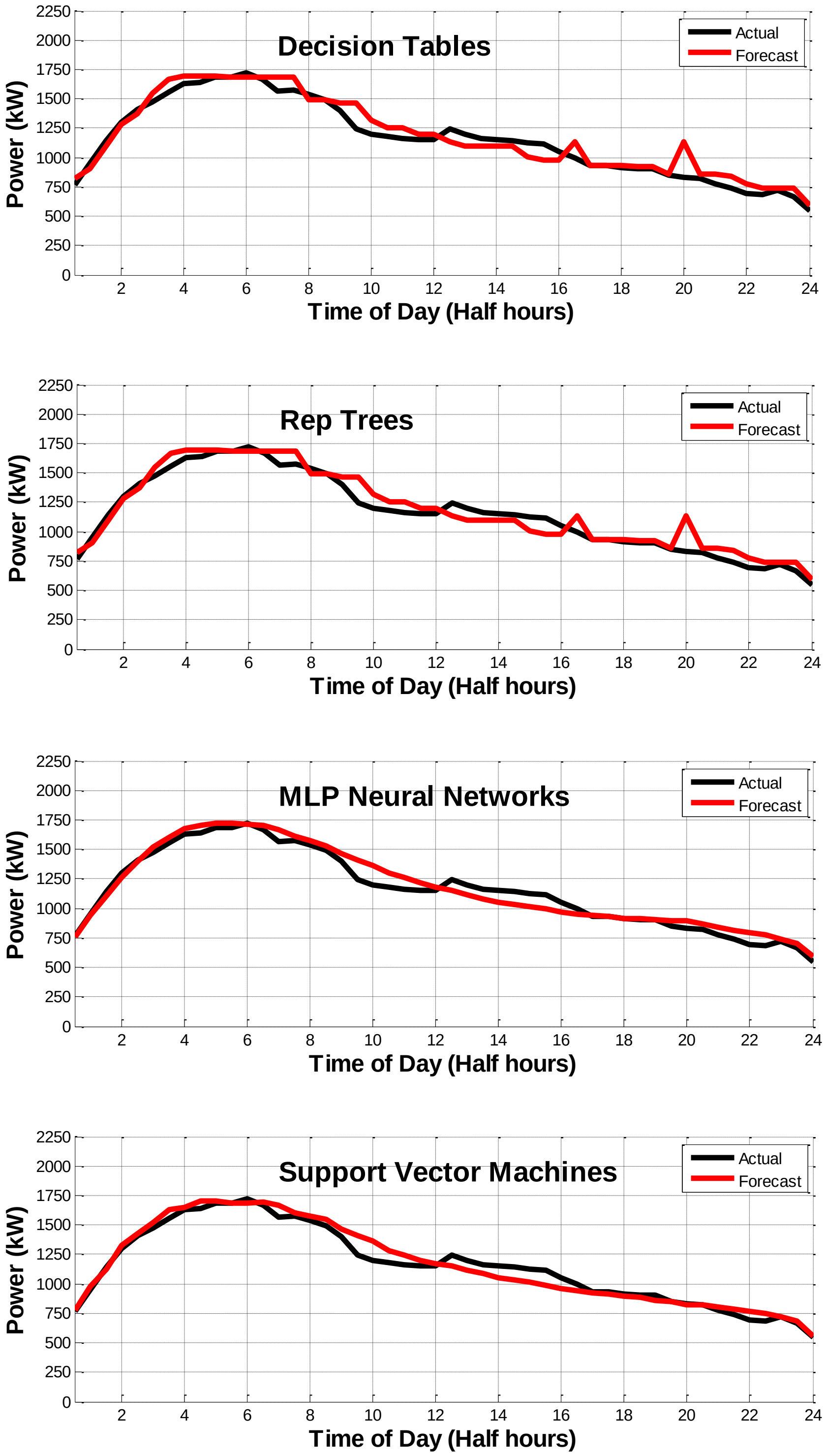

Figure 4.10 Charging Demand Forecasts

Table 4-5: Performance measures for each method

Performance index	Decision Tables	Rep Trees	MLP ANNs	SVM
MAPE (%)	6.407	5.675	5.387	4.616
RMSE	87.73	83.99	70.92	67.05
r-Correlation (%)	96.69	96.83	97.84	98.09
Training Time (s)	0.7	0.22	26.71	48.89
Testing Time (s)	0.64	0.25	27.01	48.25

As seen in Table 4-5, MAPE ranges between 4.616% - 6.407% among all different methods. In [91], it is stated that the cost of a 1% increase in the forecasting error was 10 million pounds per year for the British power system. Although all different data mining methods provide similar accuracy levels, the duration for the training processes of each method were comparatively very different. Less than one second was the training time for Decision Tables and Rep Trees while MLP ANNs and SVM needed half and one minute respectively. Although this difference is proportional very big, it remains very small for a real application. Considering that a DNO will perform a one day ahead forecast, the training time of one minute is very small to affect the procedure.

4.2.6.2 Case Study 2: Public charging stations in France

The proposed methodology is applied on a dataset coming from real charging events recorded from public charging stations. The data are from a pilot project in Paris involving 71 EVs. The EVs' charging activities were recorded for one year. The period that these charging events took place was from April 2011 until February 2012.

4.2.6.2.1 Data Description

The charging events were classified based on the ID of each EV and examined individually. For each EV, charging patterns like the connection/disconnection time and the energy demand per charging event were analysed in order to produce weekly distributions of that characteristics.

An example of the charging demand distribution of four random EVs for one week is shown in Figure 4.11.

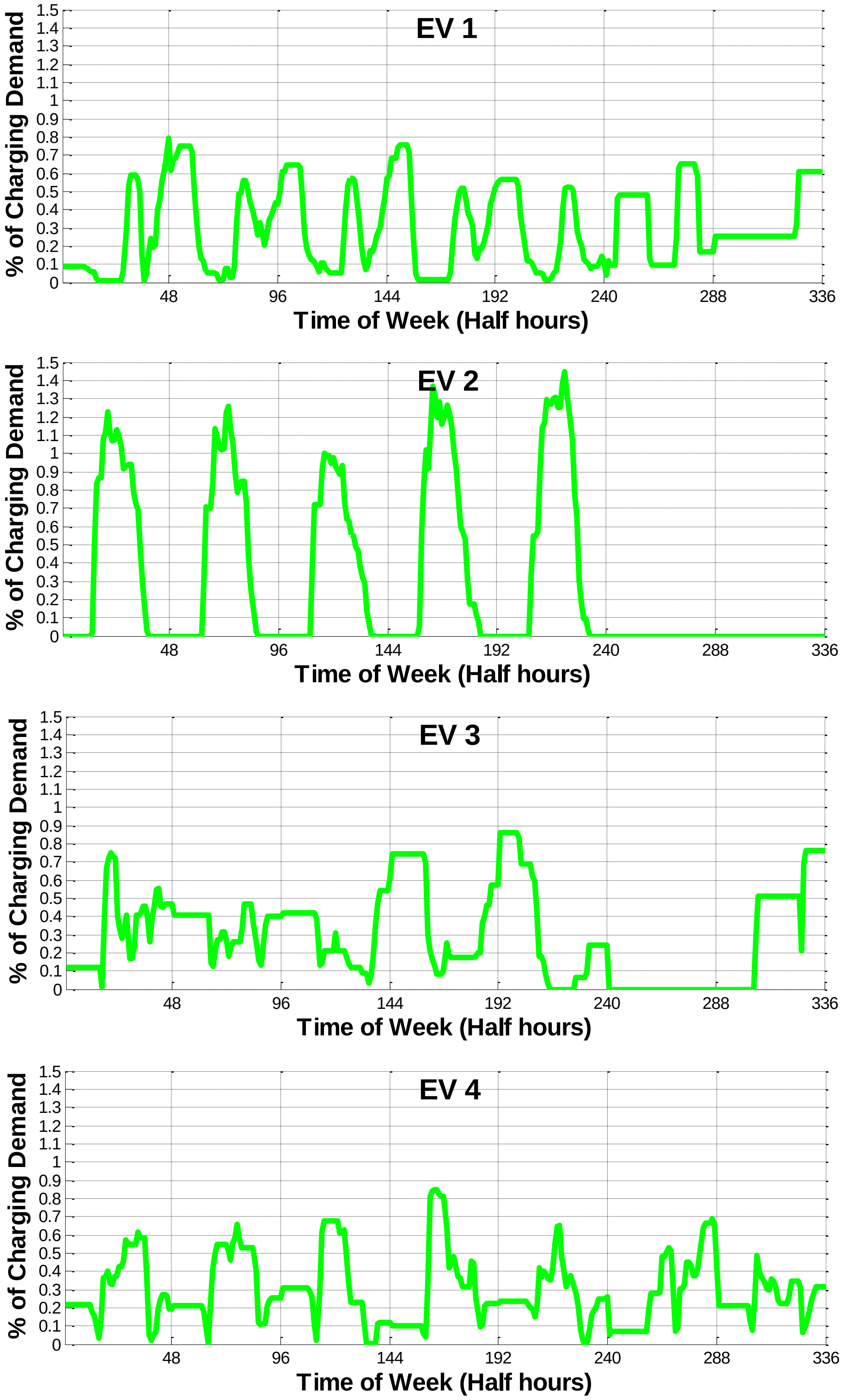

Figure 4.11: Charging Demand distribution for one week

These distributions are important for analysing the charging demand profile of each EVs owner. Useful information is also extracted analysing the distributions for the times the EVs owners connect and disconnect their vehicles to a public charging station. Due to the small size of this sample, a generalisation was necessary in order to build a larger EVs fleet. The distributions of the analysed features were used to create EVs with similar charging demand profiles. In this scenario 2,130 EVs were created and the total charging demand of this fleet was calculated for one year. This charging demand was used as input to the forecasting model. Based on the available information in the initial dataset, the attributes used for the training and testing procedures are shown in Table 4-6.

Table 4-6: Attributes used for the training process

Attribute Name	Description
Previous Week Load	The charging demand of the same day of previous week for each half hour
Week	Number of the week (1-53)
Day	Number of the day (1-7) starting with Monday
Half Hour	1-48 half hour parts of each day
Number of New Connections	The new EV plug-in connections for every half hour

Once the dataset is properly formed, the last day is considered "unknown" and constitutes the target of the forecast. The rest of the data are split in training and testing datasets and the next stage is the forecasting process.

4.2.6.2.2 Results

Using again the same procedure as described in Figure 4.6, the forecasts for one week were produced using the four data mining methods.

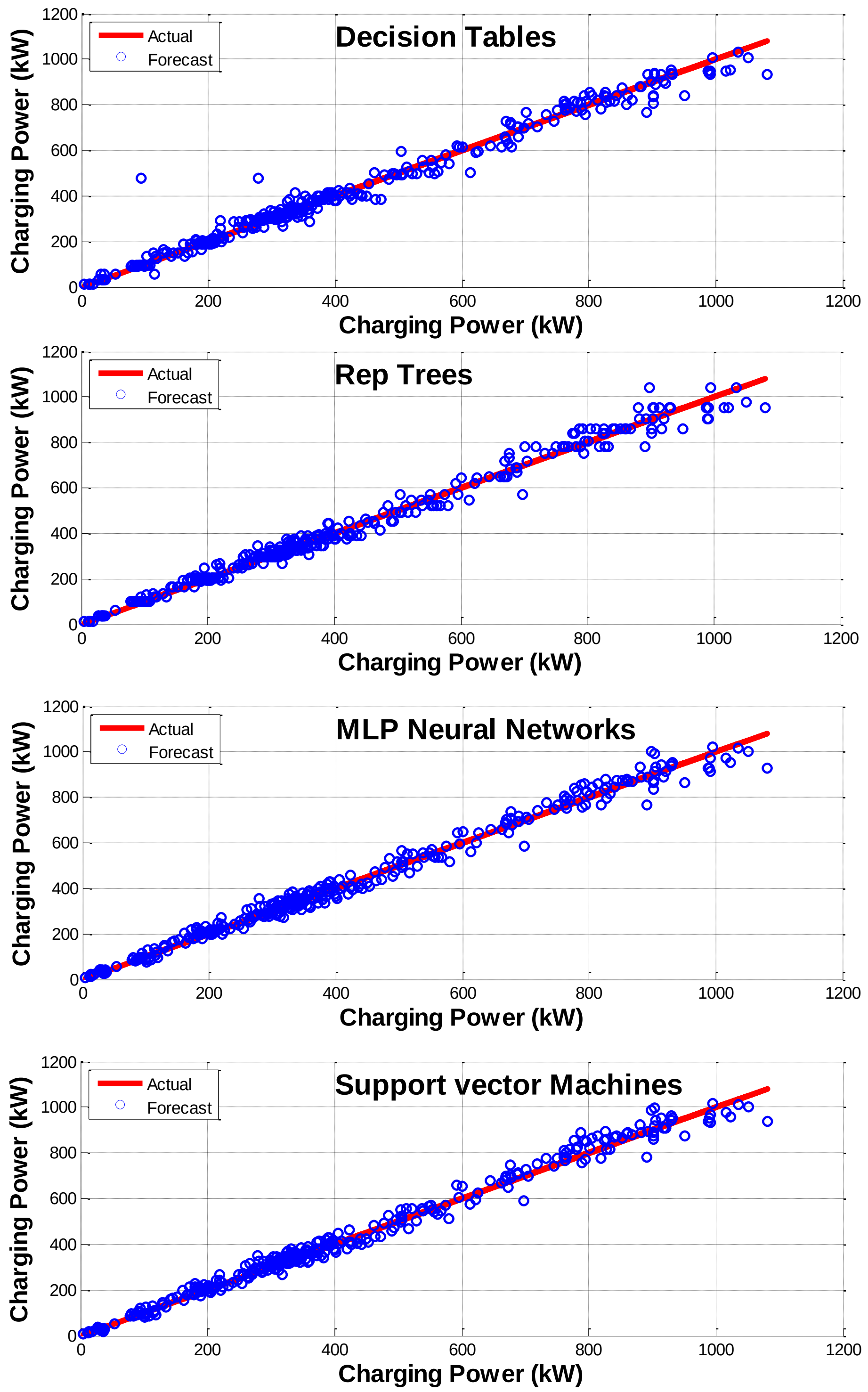

Figure 4.12: Correlation plots for each method

The correlation plots between the forecast and the actual values are represented in Figure 4.12, while the performance measures for each method are summarised in Table 4-7.

Table 4-7: Performance measures for each method

Method Index	Decision Tables	Rep Trees	MLP ANNs	SVM
MAPE (%)	7.975	6.850	6.975	6.74
RMSE	37.64	30.63	23.44	21.64
r-Correlation (%)	98.97	99.31	99.36	99.39
Training Time (s)	0.28	0.13	91.59	55.72
Testing Time (s)	0.09	0.08	0.11	1.06

The above results showed that the MAPE increased compared to the previous case study. This is justified by the fact that the charging events on this case occurred in public charging stations. The fluctuation and randomness of these events are higher than in the residential charging stations and so the relative errors increase.

SVM provided again the most accurate forecast, but Rep Trees can reach almost the same accuracy needing zero time. As mentioned before, a training time of less than one minute does not affect the appropriateness of this model for real world tasks. Obviously, there is a trade-off between accuracy and training time, which implies that more complex methods require more time to provide a more accurate forecast.

Considering that the charging events were recorded from public stations and present high fluctuation, the performance of SVM was considered accurate enough. Additional information and attributes may increase the accuracy of the forecast. Weather data when available can be used to reduce the errors of a forecast. However, adding more attributes could increase the risk of finding irrelevant connections between the data and reduce the learning capability of the model. Therefore, several trials are necessary to achieve the best results involving different datasets.

4.3 A FORECASTING MODEL FOR RENEWABLE ENERGY GENERATION

RES are seen as a promising solution to decrease GHG. However, a higher proportion of fluctuating RES such as wind power in the generation mix insert uncertainties to the electric power system due to their variability. The most significant challenge is associated with the generation unit commitment, which determines the on/off states and the output power of each generator unit for the next day [92].

In contract to conventional ICE vehicles, EVs charging management does not only provide ancillary services such as peak power reduction and frequency regulation, but also offer higher potentials for utilising locally generated renewable energy which also results in lower operating costs [93]. The development of smart grids allows the effective integration of higher share of RES in the generation mix by utilising the charging flexibility of EVs. This flexibility comes from the fact that EVs remain parked most of their time while EVs owners only require to have their vehicles fully charged when they departure.

Several studies have demonstrated the benefits of coordination between wind power generators and EVs in power networks. In [94] a model is developed to manage energy exchanges between EVs load and wind generation utilities participating in the day-ahead energy, balancing, and regulation markets. The uncertainties associated with wind power forecasting are assumed to be provided to the EV aggregator. These wind power forecasts are used to design the optimal bidding strategy model for mitigating wind energy and EV imbalance threats, resulting in optimised EV charging profiles. In [95] an adaptive algorithm is developed to control EVs charging demand aiming to balance the available wind power production. The uncertainties regarding the wind power is modelled using a Markov Decision Process (MDP).

The importance of modelling the uncertainties associated with the renewable generation in order to effectively manage the EV charging demand were demonstrated in [94] and [95]. Apparently, the future knowledge of the local renewable energy generation is important to a charging energy management system. To this end, the EV aggregator must develop appropriate forecasting techniques to effectively estimate the day ahead renewable generation in order to plan the appropriate charging strategy.

The next sections present the modelling framework for generating stochastic forecast scenarios using only historical time series data. This model can be used by the EVs Aggregator to produce stochastic forecasting scenarios for the day ahead renewable generation in a geographical area. The model is applied on real wind power time series data in order to demonstrate its performance.

4.3.1 Methodology

A generalised model was developed to produce forecast stochastic scenarios based only on the historical data values of a times series. As shown in Figure 4.13, the model consists of three stages: *Data pre-processing*, *Training* and *Forecasting*.

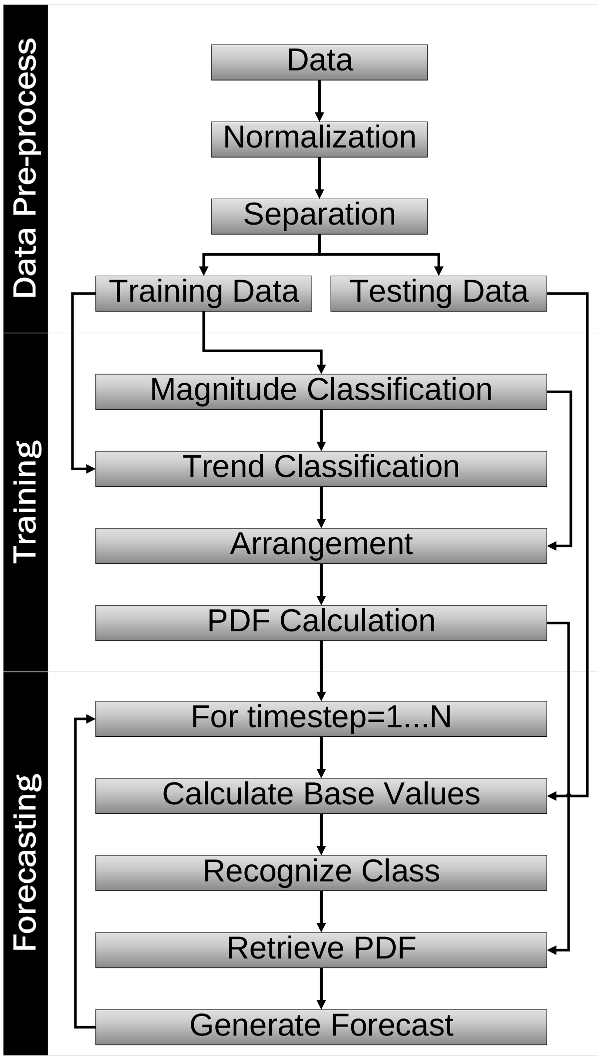

Figure 4.13: Flowchart of the model

4.3.1.1 Data Pre-processing Stage

A data pre-processing stage is required to prepare the inputs for the model. In this stage, the time series data are normalised between zero and one, based on the maximum value of the time series data. Then, the normalised data were separated in two datasets, namely *Training* and *Testing* dataset. The *Training* dataset was used in the Training process where the model finds the hidden correlations and patterns behind the data. The *Testing* dataset represents the actual data and was used to evaluate the performance of the model. The largest part of the data forms the Training Dataset whereas the rest are used in the Testing dataset.

4.3.1.2 Training Stage

During the Training stage, the relationship between two consecutive values of the training dataset is identified. Each value of the time series is classified according to its magnitude and trend. A number of N equal intervals (between zero and one) is used to classify the magnitude classes of the normalised values of the time series. For the trend classification, there are three possible classes, namely “Increase”, “Decrease” and “Constant”. In order to determine the trend class of a specific value of the time series, the magnitude class of the previous value is considered. If the previous value belongs to smaller or larger magnitude interval, then the trend class is either “Increase” or “Decrease” respectively. If both values belong to the same magnitude interval, then the trend class of the most recent value is considered as “Constant”. Figure 4.14 illustrates the structure of the classification tree.

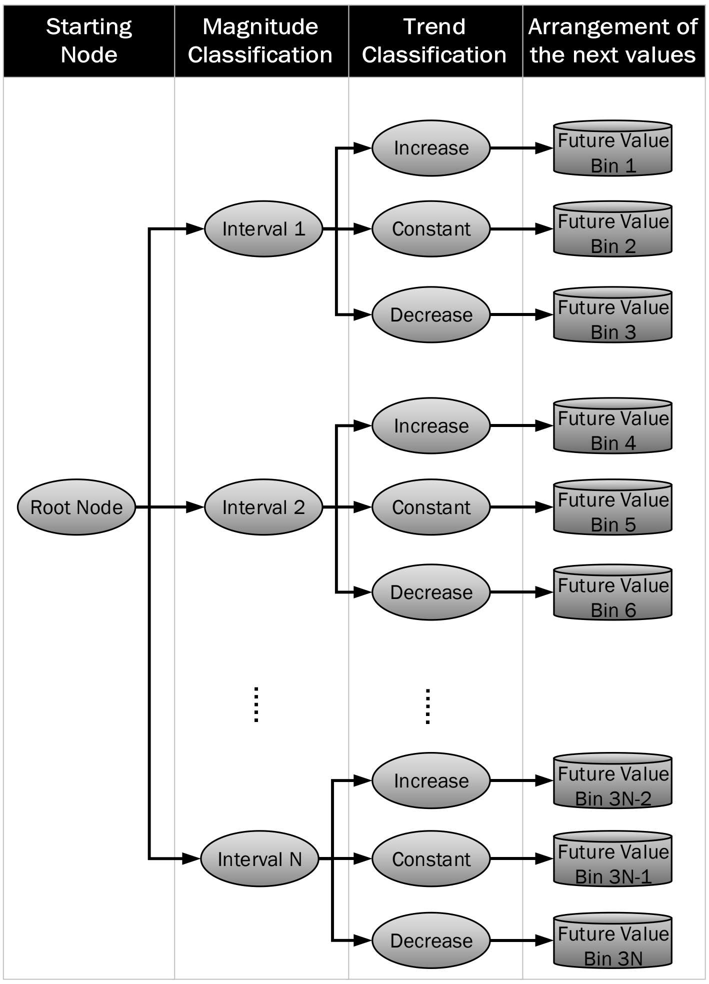

Figure 4.14: The classification tree

Based on the combination of the Magnitude and Trend classification, each value (of the time series data) is related to only one class. A "Future Value Bin" for each class is defined, containing the successor (next value) of each classified value. For example, if both the M^{th} and $(M\text{-}1)^{th}$ value of the time series belongs to Magnitude Interval N, then the $(M+1)^{th}$ value is assigned to "Future Value Bin 3N-1". This procedure is called *Arrangement.*

The final step of the training process is the calculation of the PDFs of each "Future Value Bin" group. Applying the Kernel distribution fitting methodology described in [96], the probability density function (PDF) of the data in these groups is calculated using Eq. (4.5). The kernel distribution is defined by a weight function $K(x)$ and a bandwidth value h that controls the smoothness of the resulting density curve. Unlike a histogram, which discretises the data values into separate bins, the kernel distribution sums the weight functions for each data value to produce a smooth, continuous probability curve. In this model, the Epanechnikov kernel weight function is used, described in Eq. (4.6). The bandwidth value *h* is considered equal to 2.

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \qquad (4.5)$$

$$K(x) = \begin{cases} \frac{3}{4}(1 - x^2) & ,|x| \leq 1 \\ 0 & ,otherwise \end{cases} \qquad (4.6)$$

The training process is summarised with the following algorithm. A sample of the MATLAB code used for the training process is also presented in Appendix C.

Algorithm 1: Training

Classification and Arrangement

```
for i = 2..(N_train -1) do
        for Magnitude = interval: interval: 1 do
            if Train_Data (i) < Magnitude then
                if Train_Data (i-1) > Magnitude then
                        Trend ← 'Decrease'
                elseif Train_Data (i-1) < Magnitude- interval
                        Trend ← 'Increase'
                else
                        Trend ← 'Constant'
                end if
             ClassID←class.(Magnitude).(Trend).FutureValueBin
             push Train_Data (i+1) to ClassID
             break
           end if
       end for
end for
```

PDF Calculation

```
for Magnitude = interval: interval:1 do
        for round = 1..3 do
            if round=1 then
                Trend ← 'Decrease'
             elseif round=2
                Trend ← 'Increase'
             else
                Trend ← 'Constant'
             end if
             Data ← class.(Magnitude).(Trend). FutureValueBin
             PDF_ID← class.(Magnitude).(Trend).PDF
             push KernelDensityFunction(Data) to PDF_ID
         end for
end for
```

4.3.1.3 Forecasting Stage

This model generates the next time step normalised value considering the two most recent time steps. The normalised values of these two time steps are defined as *base value1* (one-time step before) and *base value2* (two-time step before) respectively. The model first recognises the Magnitude of both base values and then identifies the Trend Class of *base value1*. Once the class of *base value1* is recognised, the model retrieves the parameters of the corresponding PDF. A random number is then generated following the specific PDF. This process is repeated for the whole forecasting period (N time steps), using the two most recent generated values to produce the value of the next time step.

The values of the future time steps are generated using a rolling process. Every generated value of a time step is considered as the *base value1 to* produce the value for the next time step. This results in less accurate predictions as the forecast time horizon increases. The generated value of the first time step introduces an error which is transferred to every consequent generated value. To overcome this problem, this model updates regularly the base values using the two past time steps actual values of the time series data. Frequent updates of the base values result in decreased forecasting errors, however the computation cost is increasing. Therefore, this number is defined subject to the desired accuracy levels or the computational limitations. Due to the occurrence of larger errors in further ahead time steps, the impact of updating the model using the most available data is worthwhile to be explored. However, it is out of the scope of this research work to analyse the computational cost when increasing the frequency of updating this model.

Algorithm 2 describes the detailed actions in order to produce the value of the next time step using the PDFs calculated during the Training stage. In this algorithm, two tasks are implemented namely, *Base Values Calculation* and *Random Value Generation*. A list containing the numbers of the future time steps (of the Testing Period) when the model needs to update its Base Values is assigned to an "*UpdateFrequency"* variable.

For the first time step of the forecasting period, the last two values of the Training dataset are used to complement the base values. For the remaining time steps, the model checks if the current time step is included in the "*UpdateFrequency"* list. In case the current time step is included in the "*UpdateFrequency"* list, the actual time series values of the two previous time steps are used to describe the *base value1* (one-time step before) and *base value2* (two time steps before). In the specific case when the current time step is equal to the second time step of the Testing period, the model uses the last time step of the Training Dataset as *base value2* and the actual value of the first time step (of the Testing period) as *base value1*. In case the current time step is not included in the “*UpdateFrequency”* list, the actual values of the two past time steps are used as *base value1* (one-time step before) and *base value2* (two time steps before) respectively. The *Base Values Calculation* task is described with lines 2-16 of the Algorithm 2.

Once the *Base Values Calculation* task is complete, the next stage is the *Random Value Generation.* First, the model identifies the Magnitude Class of *base value1* and then compares it with the Magnitude Class of *base value2*. According to Magnitude Class and Trend Class of *base value1*, the parameters of the corresponding PDF are retrieved. A random number is generated using these parameters, which is the forecasted value for the current time step. This process is described with the lines 17-31 of Algorithm 2. A sample of the MATLAB code used for the production of the stochastic forecast scenarios is presented in Appendix C.

Algorithm 2: Forecasting

```
for ts = 1..N_test do
Base Value Calculation
        if ts = 1 then
            base_value1 ← Train_Data (N_train)
            base_value2 ← Train_Data (N_train -1)
        elseif ts mod UpdateFrequency = 0
            if ts=2
                base_value1 ← Forecast_Data (ts-1)
                base_value2 ← Train_Data (N_train)
            else
                base_value1 ← Test_Data (ts-1)
                base_value2 ← Test_Data (ts-2)
            endif
        else
            base_value1 ← Forecast_Data (ts-1)
            base_value2 ← Forecast_Data (ts-2)
        endif
Random Value Generation
        for Magnitude = interval: interval: 1 do
            if base_value1 < Magnitude then
                if base_value2 > Magnitude then
                        Trend ← 'Decrease'
                elseif base_value2 < Magnitude- interval
                        Trend ← 'Increase'
                else
                        Trend ← 'Constant'
                endif
                PDF_ID←class.(Magnitude).(Trend).PDF
                NewForecast←RandomGenerator()
                Forecast_Data(ts)← NewForecast
                break
            endif
        endfor
endfor
```

4.3.2 *Case Study*

4.3.2.1 Data Description

The model was applied on real aggregate wind power data, obtained from [www.elexon.co.uk]. The data consisted of 10,416 half-hourly aggregate wind power values from wind farms across the Great Britain, for the period of 01/3/2014 to 3/10/2014. Figure 4.15 shows the time series of the actual wind power and its first difference over time.

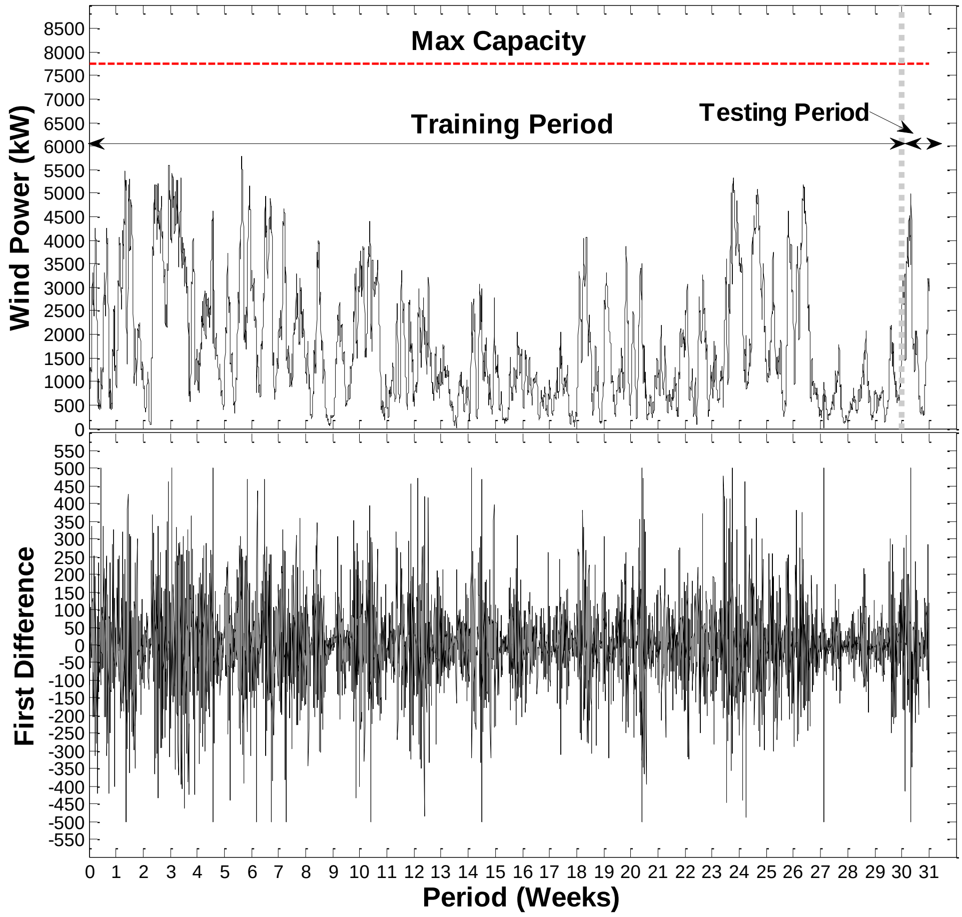

Figure 4.15: Times Series of the aggregate wind power and its first difference

The data were pre-processed following the methodology of Figure 4.13. The total installed capacity of wind farms across GB throughout the whole period under study (31 weeks in total) was used to normalise the data. The normalised data were separated in two groups, the Training and the Testing datasets. Data from the first 30 weeks were used as the Training dataset whereas data from the last week were used as the Testing dataset. Some analysis metrics are presented in Table 4-8.

Table 4-8: Descriptive Statistics

Index	Value
Mean (kW)	1720.711
Standard Deviation (kW)	1281.504
Average Rate of Change (%)	17.06
Max Wind Power (kW)	5786
Min Wind Power (kW)	1
Capacity of wind farm (kW)	7740

During the training process, the training data were classified based on their magnitude and trend. Intervals of 0.01 (normalised wind power) were used in the magnitude classification, whereas the trend was determined by comparing with the previous data entry. The classification tree consists of 300 classes (leaves), and consequently 300 "future" groups.

4.3.2.2 Performance Indices

The penetration of wind generation is expected to increase in the following years due to environmental and energy security reasons. However, wind power is high fluctuating and unmanageable. Short term forecasting of the wind power up to 48 hours is important for its large scale integration to the national generation mix of each country. Therefore, it is important that a wind power forecasting model is properly evaluated. A review of the evaluation criteria for wind power forecast is described in [97]–[100]. In this work, the following evaluation criteria used for the performance of the forecasting model are listed below:

Mean Error (ME)

$$ME_k = \bar{e}_k = \frac{1}{N}\sum_{t=1}^{N} e_{t+k|t} \tag{6.3}$$

Normalised Mean Absolute Error (NMAE)

$$NMAE_k = \frac{1}{P_{\max}} \cdot \frac{1}{N} \cdot \sum_{t=1}^{N} \left| e_{t+k|t} \right| \tag{6.4}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE_k = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{P_{t+k} - \widehat{P}_{t+k}}{P_{t+k}}\right| \cdot 100\% \quad (6.5)$$

Standard Deviation of the Errors (SDE)

$$SDE_k = \sqrt{\frac{\sum_{t=1}^{N}\left[e_{t+k|t} - \bar{e}_k\right]^2}{N-1}} \quad (6.6)$$

Where:

$e_{t+k|t} = P_{t+k} - \widehat{P}_{t+k}$ is the error corresponding to time $t+k$ for the prediction made at time t

P_{t+k} is the time series value at time $t+k$

$\widehat{P}_{t+k}$ is the forecasted value for time $t+k$ made at time t

$P_{\max}$ is the maximum value of the time series

N is the number of prediction errors used for method evaluation

Any prediction error consists of a systematic μ_e and random χ_e, where μ_e is a constant and χ_e is a zero mean random variable. Mean Absolute Error (MAE) is affected by both systematic and random errors whereas only random errors affect the SDE criterion which describes the error distribution. MAE presents robustness when large prediction errors exist [98]. This criterion is essential to be included in the error evaluation of a forecasting model.

4.3.2.3 Results

After the training process, the forecasting model was used to forecast the wind power of the last week (31st) of the dataset. As mentioned before, the base values are regularly updated with the actual wind power values (Testing dataset) at a given frequency. Seven different update frequencies were considered, namely every 48, 24, 16, 12, 8, 4 and 2 half-hourly time steps. The forecasting model was run 20 times for every update frequency, resulting in 140 forecasts in total for the 31st week of the dataset. The results are shown in Figure 4.16. Table 4-7 presents the performance indices which were used to evaluate the accuracy of the forecast.

Table 4-9: Performance Indices

Update Frequency	**Index**	**Day1**	**Day2**	**Day3**	**Day4**	**Day5**	**Day6**	**Day7**
Every 48 time steps	MAPE	32.79	53.45	41.86	35.75	172.08	68.83	44.96
	SDE	0.1	0.12	0.16	0.07	0.11	0.05	0.07
	NMAE	0.14	0.34	0.19	0.1	0.15	0.05	0.17
Every 24 time steps	MAPE	29.2	32.76	45.19	34.09	72.75	44.69	28.54
	SDE	0.08	0.1	0.12	0.07	0.06	0.03	0.06
	NMAE	0.12	0.19	0.19	0.1	0.08	0.03	0.1
Every 16 time steps	MAPE	31.59	23.09	29.69	24.36	41.09	37.49	22.97
	SDE	0.07	0.07	0.11	0.05	0.04	0.02	0.05
	NMAE	0.12	0.13	0.14	0.07	0.05	0.03	0.08
Every 12 time steps	MAPE	23.01	19.92	18.96	24.7	34.78	39.41	18.8
	SDE	0.06	0.06	0.08	0.05	0.03	0.02	0.04
	NMAE	0.09	0.11	0.1	0.07	0.04	0.03	0.06
Every 8 time steps	MAPE	15.46	13.38	16.24	19.45	25.23	27.97	14.53
	SDE	0.04	0.05	0.06	0.04	0.03	0.02	0.03
	NMAE	0.07	0.07	0.08	0.06	0.03	0.02	0.05
Every 4 time steps	MAPE	9.25	7.49	8.56	12.96	15.79	21.49	10.31
	SDE	0.03	0.03	0.04	0.03	0.02	0.01	0.03
	NMAE	0.04	0.04	0.05	0.04	0.02	0.01	0.03
Every 2 time steps	MAPE	6.06	4.9	5.12	8.18	10.74	14.25	7.42
	SDE	0.02	0.02	0.02	0.02	0.01	0.01	0.02
	NMAE	0.03	0.03	0.03	0.02	0.01	0.01	0.02

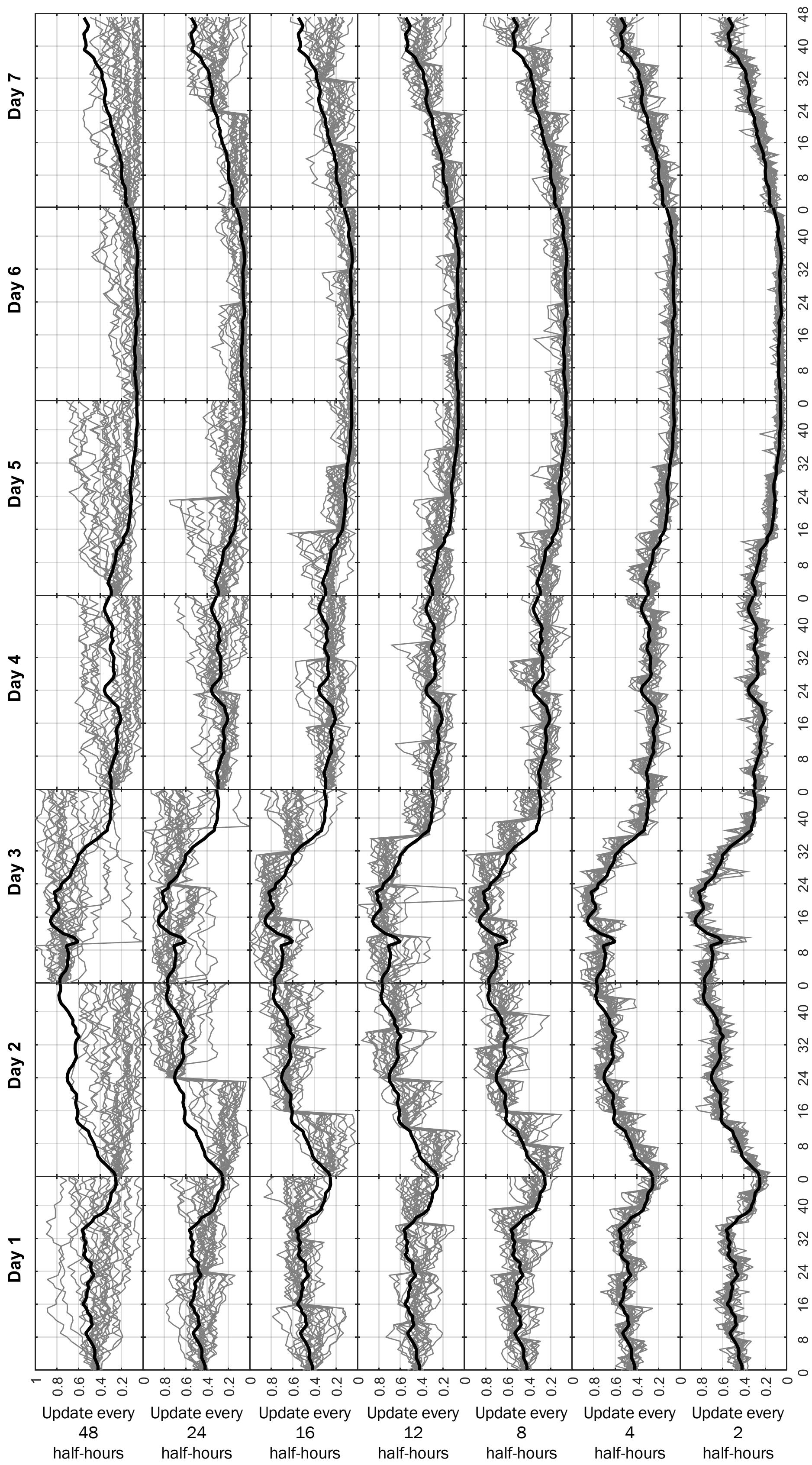

Figure 4.16: Twenty forecasts for every day and update frequency

As seen from Figure 4.16, updating the base values more frequently results in more accurate forecasts. This is also depicted in Table 4-9, where the indices show a forecasting improvement as the update frequency is increased. This is because of the chain-like behaviour of the forecasting model. An error in forecasting the first time step contributes to the next forecast, creating another error and so on. This error chain breaks when the base values are updated with the actual wind power, and the model generates the next forecast without any previous errors. The wind power on days 2 and 3 is very fluctuating; therefore, the forecasting errors are higher. On the other hand, day 6 has almost a constant wind power generation, and the forecasting errors are very low. In overall, all the performance indices are improved when the update frequency is increased. The MAPE ranges between 32.79% - 172.08% when the base values are updated every 48 time steps. When the update frequency is increased to every 2 time steps, the MAPE ranges between 4.9% - 14.25%; an average of 84.827% improvement. Average improvements of 80.657% and 85.073% are also observed for the SDE and NMAE respectively.

The performance of the proposed model was compared to Persistence Model, described in [97]. This is a reference model, widely used for wind power prediction and meteorology. The Persistence Model assumes that the future wind power production remains constant and equal to the last measured value of wind power. In Figure 4.17 the MAE of the Persistence model was compared with the proposed forecasting model when the base values are updated every 48 half hours. In Figure 4.18 the cumulative NMAE of the Persistence model is compared to the proposed forecasting model when the base values are updated every 48 half hours. The results show that as the forecast time horizon increases, the proposed model provides more accurate forecasts.

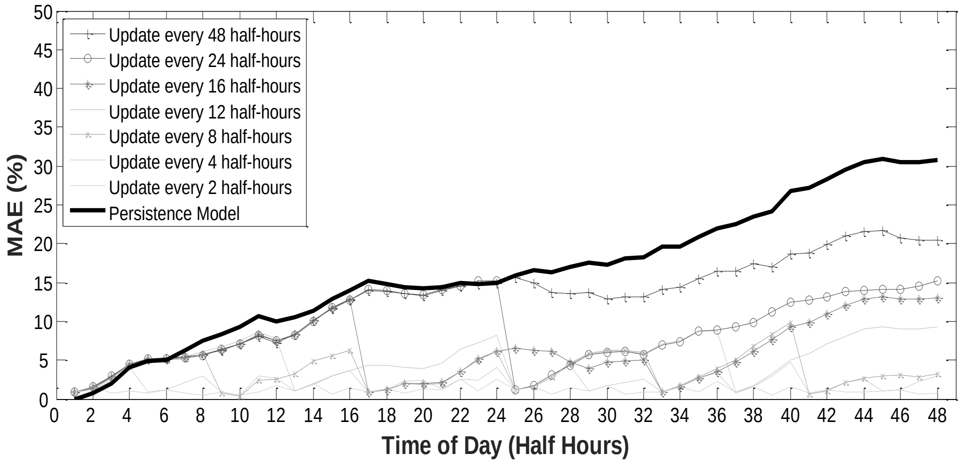

Figure 4.17: MAE for the Persistence and Proposed Model

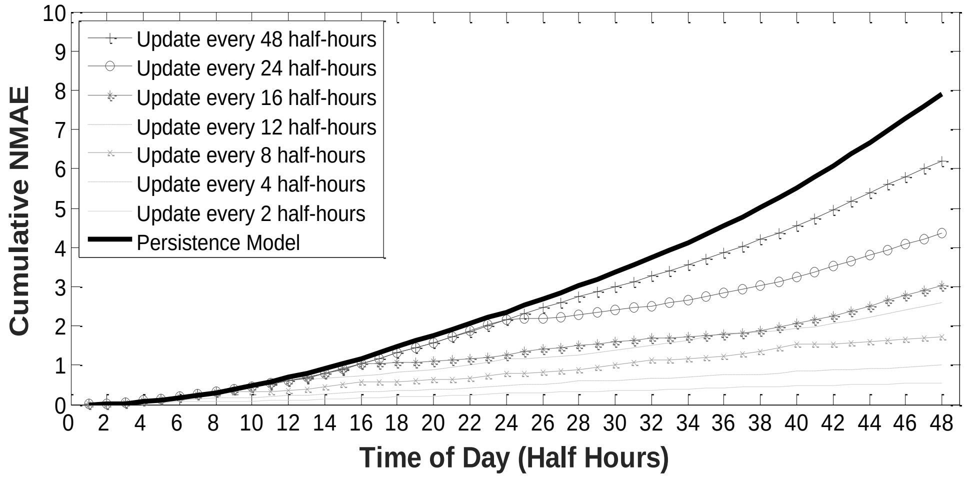

Figure 4.18: Cumulative NMAE for the Persistence and Proposed Model

Figure 4.19 presents the distribution of the error on every day of the forecasted week. On each box, the red line is the median and the edges of the blue box are the 25th and 75th percentiles. Every data point outside the box is considered outlier, and is drawn in black. The stochastic nature of the forecasting model results in different forecasted values each time.

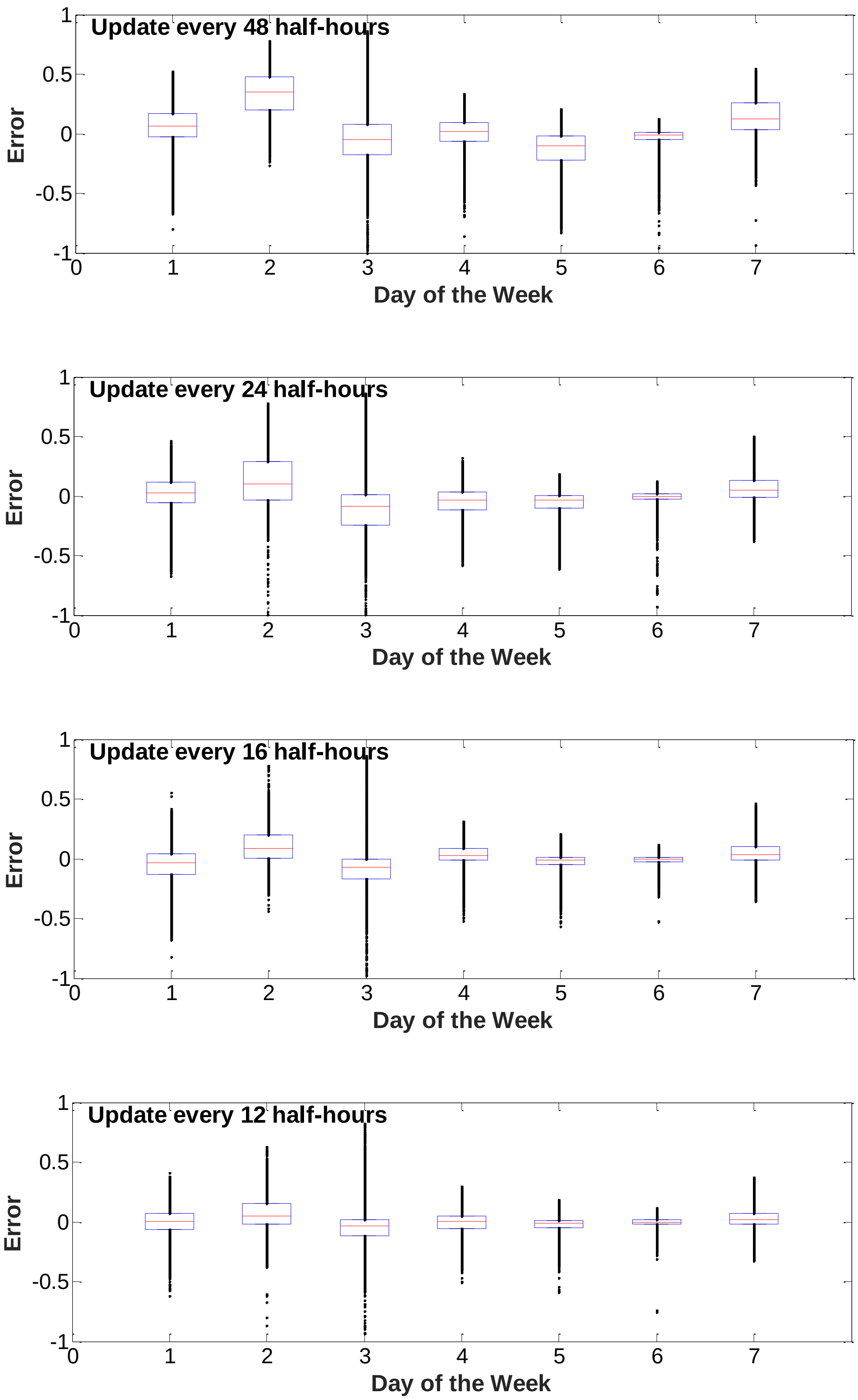

Figure 4.19: Daily error distribution

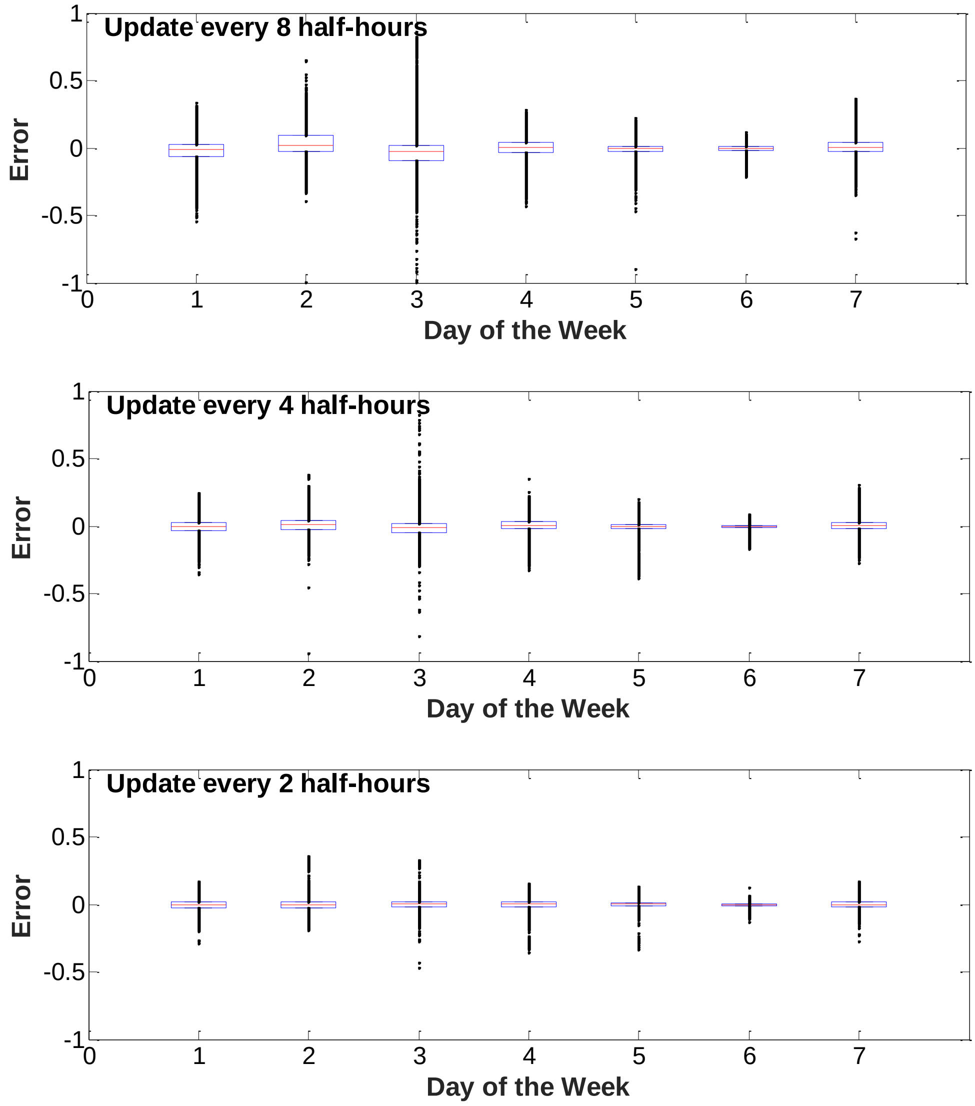

Figure 4.19: Daily error distribution (Continued)

To investigate and capture any possible systemic errors, 1000 forecasts were generated for the same week. The half-hourly forecast errors were calculated, and the results are shown in Figure 4.20. All seven days of the 31st week were considered, for every update frequency. In all cases the error median is close to zero for every half-hour, proof that there is no systemic error in the model. High update frequency results in low error range, improving the forecasting accuracy.

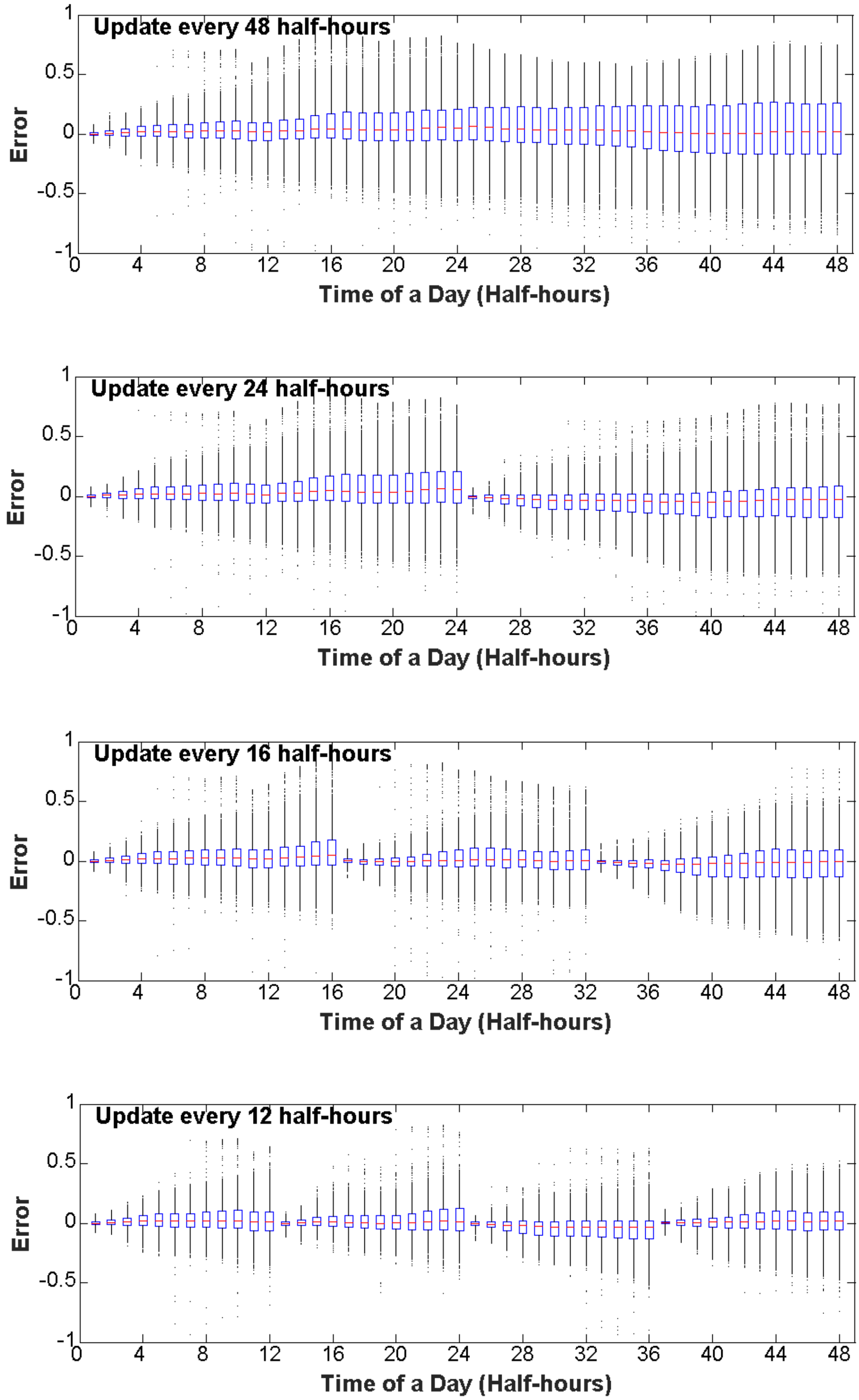

Figure 4.20: Half-hourly error distribution

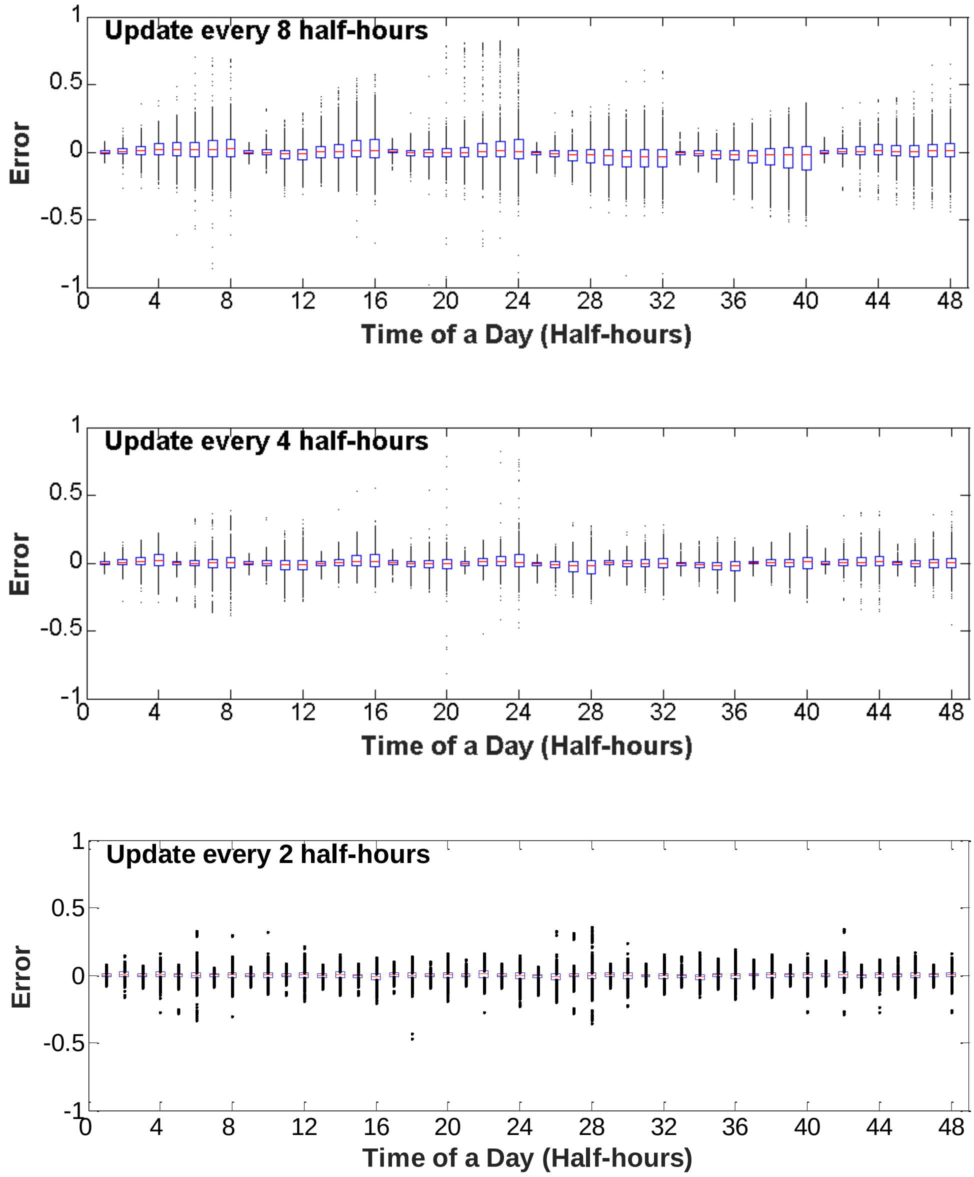

Figure 4.20: Half-hourly error distribution (Continued)

Another significant factor that affects the performance of the model is the number of magnitude intervals used in the classification stage. In order to investigate the effect of this factor, the training process was repeated for magnitude intervals of 0.1, 0.05 and 0.02. For every interval the model was used to forecast the same week (31^{st}), using the seven different update frequencies. Figure 4.21 presents the aggregated results of MAPE for each case. The effect of the size of magnitude interval depends on the update frequency. As seen from Figure 4.21, at low update frequencies there is not significant impact from the size of magnitude interval. At high update frequencies however, reducing the size of magnitude interval (increasing the number of magnitude classes) results in further improvement of the forecasting accuracy.

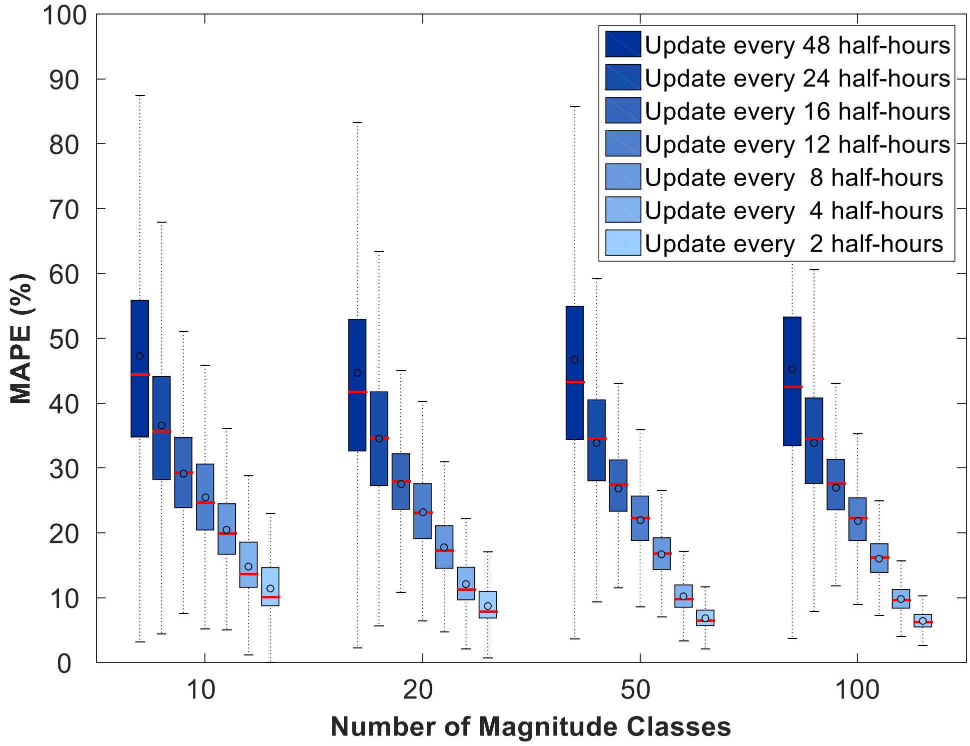

Figure 4.21: MAPE for different Rolling Update Frequencies and number of Magnitude Classes

In overall, considering 10 Magnitude Classes the average MAPE for 1000 forecasts was reduced from 44.2% to 10.15% when the update frequency increased from 48 to 2 time steps. This represents a reduction of 77.03% in the forecasting error. The accuracy can be further improved by increasing the number of Magnitude Classes used in Training Stage. Considering 100 Magnitude Classes, the average MAPE for 1000 forecasts was reduced by 84.79% from 42.3% to 6.43% when the update frequency increased from 48 to 2 time steps. In addition, increasing the number of Magnitude Classes results in a reduction on the error range. For 10 magnitude classes and update frequency of 2 half-hours the error range is 23.48%. However, for 100 magnitude classes the error range is 7.96%.

4.4 SUMMARY

In this chapter the use of data mining methods for forecasting the EV charging demand was studied. Two different realistic study cases where considered and the performance of four different data mining methods was evaluated. In the first study case the day-ahead charging demand of 3,000 EVs was forecasted and compared to the actual data. The second study case considered a fleet of 2,130 EVs and predicted the charging demand of a whole week on a half-hourly basis. The results showed that data mining methods can be used for forecasting the EV charging load, with increased accuracy especially when the configuration parameters of each method are carefully selected. However, more cases have to be studied, in order to clearly understand the key attributes that indicate the choice of one data mining method over another. The proposed forecasting model for the EVs charging demand was part of the charging control algorithms described in Chapter 5 and Chapter 6.

In addition, a model was developed for producing day-ahead probabilistic generation forecast scenarios. Using a rolling forecasting approach, the impact of frequent updating of the forecasts was investigated. The modelling framework consisted of three parts, Data pre-processing, Training and Forecasting. The Data pre-processing stage included a data normalisation. The training stage is related to the extraction of the knowledge hidden behind the wind power data. Each normalised data point was classified according to its magnitude level and trend. For every combination of the above classes, the PDFs were calculated using kernel density estimators. Finally, the model provides probabilistic rolling forecasts for the next time step according to the Magnitude classes of the two previous time steps and the Trend Class of the previous time step. This rolling forecasting model is updated in a regular basis, increasing its accuracy. It was demonstrated that increasing the number of magnitude classes together with the update frequency results in more accurate forecasts. This impact of various data updating frequency on the accuracy of the forecasts was investigated. The results showed an improvement of the forecast accuracy as the model updates the base values more frequently. Although this forecasting model was tested on wind power data, its main advantage is its universal design which makes it applicable to any time series data (PV power times series, etc.). A charging controller can utilise the output of this model in order to plan the appropriate charging strategy and coordinate EVs to charge preferentially from RES. However, for ease of implementation of the EVs smart charging controller described in Chapter 6, PV forecasts were assumed to be provided due to lack of sufficient amount of historical PV power data.

CHAPTER 5

SMART MANAGEMENT OF ELECTRIC VEHICLE CHARGING ENHANCED BY ELECTRIC VEHICLE LOAD FORECASTING

5.1 INTRODUCTION

The continuous growth and evolve of vehicle electrification causes the electric power systems to confront new challenges, since the load profile changes, and new parameters are being set. With the number of EVs gradually rising, problems may occur in technical characteristics of the network, like bus voltages and line congestion [6].

In order to prevent grid technical violation and avoid early reinforcements of existing infrastructure, it is necessary to develop EVs management systems so as to prevent such phenomena. The effectiveness of such systems is heavily depended on the early knowledge of future demand. This knowledge can be provided by accurate EVs load forecasting techniques.

This chapter presents a control algorithm to manage the EVs charging requests. The aim of the control algorithm is to achieve a valley-filling effect on the demand curve, avoiding a potential increase in the peak demand. The proposed control model utilises the EVs forecasting model described in Chapter 4. This incorporation of the forecast model to EVs charging management contributes to the effectiveness of the charging control model. Through different case studies, the performance of the proposed model is evaluated and the value of the EVs load forecasting as part of the EVs load management process is illustrated.

The rest of the chapter is structured as follows: Section 5.2 indicates the importance of EVs load forecast to the management of the EVs charging. Also, Section 5.3 presents the integrated proposed model in detail as well as the operation of the main entities of the model. Section 5.4 presents the simulation results and the effectiveness of the integrated model is evaluated. Finally, a summary is given in Section 5.5.

5.2 THE IMPORTANCE OF THE EVS LOAD FORECAST

The majority of charging control models assumes that all EVs are participating in the control scheme. However, this is not a realistic scenario for the future composition of the EVs fleet. In a realistic case, the EVs fleet is separated in “Responsive” and “Unresponsive” EVs to control signals coming from the aggregator. “Responsive” EVs are the ones that participate in coordination process responding to control signals from the EVs aggregators or other central management entities. On the contrary, “Unresponsive” EVs are not willing to participate in the control scheme. This willingness to participate in the control scheme is defined by the EVs owners and their routine. For example, if the daily routine of a EVs owner is affected due to an event, this may also influence the flexibility in charging the vehicle. Note also that some EVs can be responsive to control signals in most cases. However, this does not mean that abnormal charging events are not happening occasionally from the same EVs. Forecasting the demand from “Unresponsive” EVs is critical for the effectiveness of the control scheme. Historical charging events are used to extract information about the abnormal charging demand from “Unresponsive” EVs. The value of EVs load forecast to the control of EVs charging is illustrated through an example. In this example a mixture of “Responsive” and “Unresponsive” EVs is assumed. The arrival and departures times of both types of EVs are shown in Figure 5.1a. An abnormal event occurs at 10:00, when a number of “Unresponsive” EVs are connected to the charging stations requiring charging for a short period of time. Despite other EVs (the responsive ones) having a level of flexibility for the connection time, the inflexible demand from the “Unresponsive” EVs is critical for the effectiveness of the control algorithm.

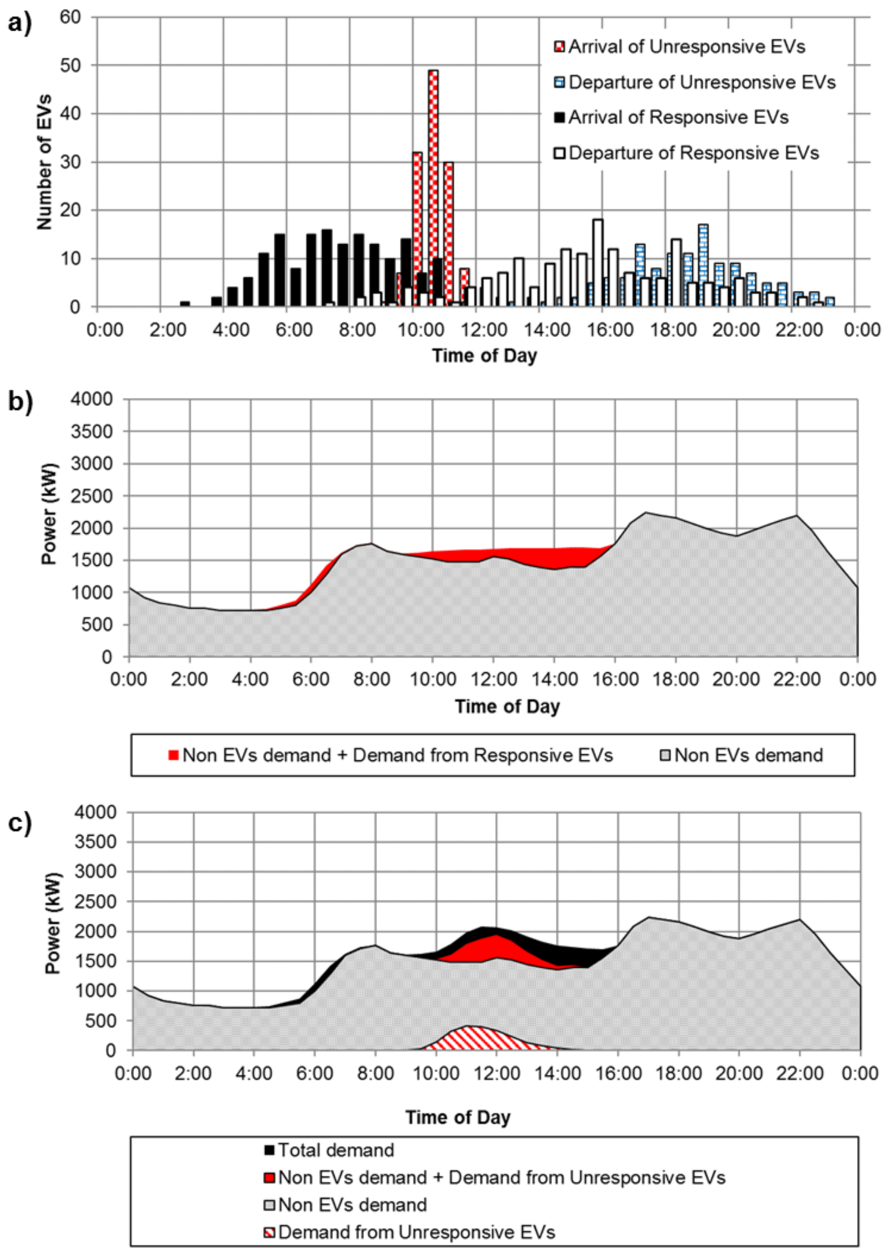

Figure 5.1: a) Distributions of arrival and departure times of "Responsive" and "Unresponsive" EVs b) Demand without adding the demand from "Unresponsive" EVs, c) Total Demand

In this example, a control algorithm was applied to coordinate all EVs without having future knowledge of the demand from the "Unresponsive" EVs. The objective of this control algorithm is to have a valley-filling effect on the demand curve of the assumed network. Figure 5.1b shows the final demand from the "Responsive" EVs. Based on the control model, a number of EVs were responsive to the control signals and as a result they are coordinated to charge at times when the demand is low. However, in a mix scenario like this example, without forecasting the demand from the "Unresponsive" EVs, the final result of the coordination algorithm is not optimal. Figure 5.1c indicates this weakness of the majority of the control models proposed in the literature.

5.3 THE INTEGRATED MODEL FOR CHARGING MANAGEMENT OF EVS

A control algorithm was developed to manage the EVs charging schedules, enhanced by EVs load forecast. The aim of the control algorithm was to achieve a valley-filling effect on the demand curve, avoiding a potential increase of the peak demand. The structure of this model follows the architecture of a MAS where each entity is an agent. An agent is categorised as active when its activities aim in achieving a goal in the system whereas an agent which does not affect the system with its actions is called passive agent [101]. In this model, there are two active agent classes, the EVs agent and the EVs aggregator agent whereas the passive one is the DSO agent.

Figure 5.2 shows the location of each entity in an example network. EVs agents are located at the LV level and each LV feeder constitutes a EVs cluster. Each EVs cluster is a group of EVs which are supplied with energy from the same LV feeder of which the technical constraints have to be respected. On the top level of the network, there is the DSO agent who is responsible to monitor the demand and voltage in the most significant parts of the network. Its role is only to provide information regarding the grid condition to the EVs aggregator without taking any decisions which affect the system. EVs aggregator is an entity which is located in an intermediate level between EVs and DSO. Based on the objectives of the control algorithm, the EVs aggregator can be located either in Medium Voltage (MV) transformer or in a LV transformer.

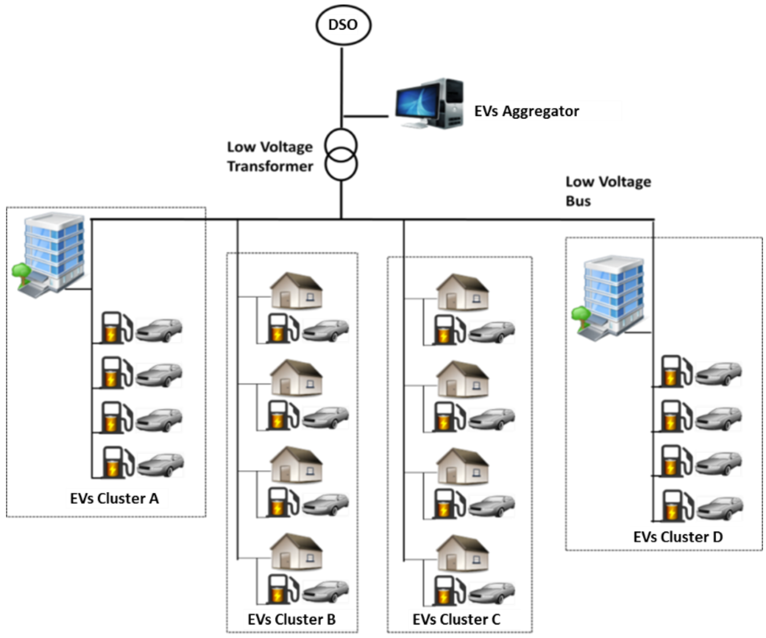

Figure 5.2 Schematic example of the charging system

The proposed control algorithm is designed based on the structure of a UK generic LV distribution network obtained from [102], without affecting the generality of the model. The EVs aggregator is located on the MV level, while the EVs agents are dispersed in the LV feeders. The EVs aggregator's role is to collect the historical charging data of the EVs fleet and apply machine learning algorithms to provide accurate forecasts of the future charging demand of "Unresponsive" EVs. The EVs Load Forecasting process uses SVM, and is executed by the EVs Aggregator to improve the effectiveness of the algorithm. The EVs are coordinated to achieve a local valley-filling effect in the demand curve of the LV feeder to which they are connected. In order to demonstrate the importance of the EVs load forecast algorithm in the proposed control scheme, different charging scenarios and composition of the EVs fleet were considered.

Figure 5.3 presents the basic operations of the EVs and the EVs Aggregator. The DSO agent provides information to the EVs aggregator regarding the technical constraints of the network. This information is linked with the maximum power demand of the corresponding feeder, transformer loading and the thermal limits of the network cables. In addition, EVs aggregator is receiving the forecasted non EVs demand of the next two days.

In the proposed model, it is assumed that none EVs owners leave their vehicles connected in a charging point for more than 24 hours.

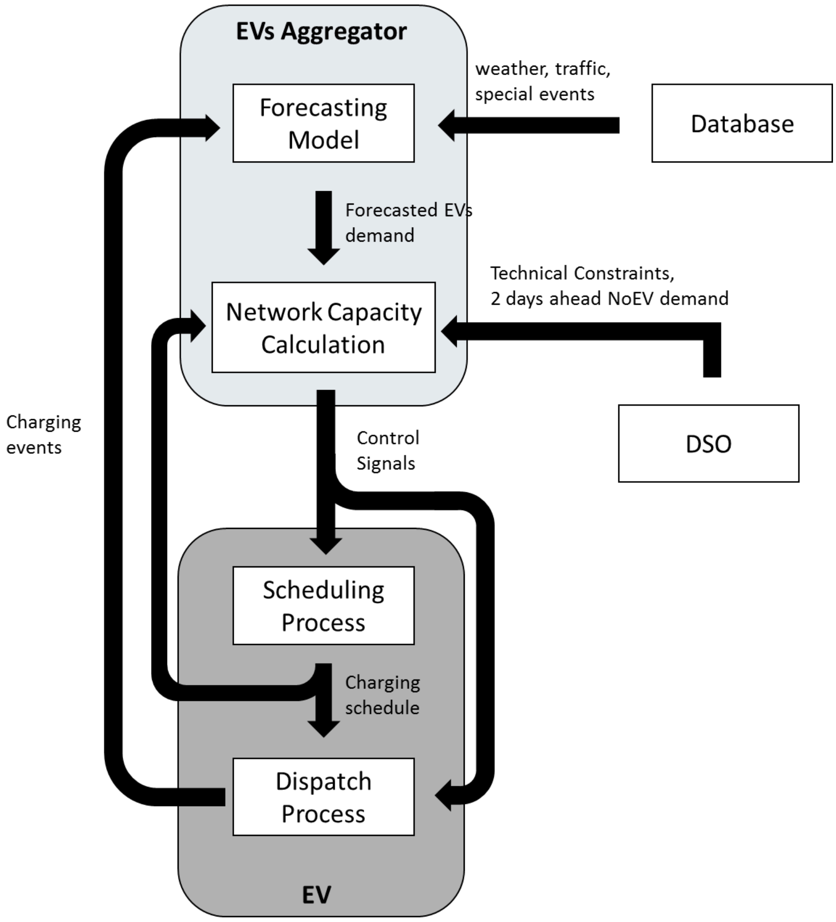

Figure 5.3: Flow of Information diagram

Initially, the EVs load forecast model is updated with charging data of the previous day. These data are processed based on the methodology presented in Section 4.2.4. Moreover, in case other sources of information like weather data or traffic measurements are accessible to the EVs aggregator, they are also included in the forecast model in order to increase the accuracy of the predictions. The forecasting model is updated with the latest data and provides the two-days ahead forecasted charging demand from "Unresponsive" EVs. Once the output of the forecast model and relevant data from DSO are available to the EVs aggregator, the next stage includes the calculation of the control signals. The EVs aggregator calculates the network's capacity for EVs charging demand based on the EVs forecasted demand. The objective of the control model is a valley-filling effect on the demand of the LV feeders. Therefore, each EVs cluster is associated with a specific LV feeder and each group of EVs receives the same control signals. These signals are related to the existing charging schedules and the predicted EVs demand for the corresponding part of the network. Based on those signals, each EV defines its own charging schedule by selecting when to charge. The charging events are recorded, and used to update the forecasting procedure.

The timeframe resolution of the proposed model is measured in time steps (e.g. 10 min interval). The time steps affect the regularity of the control actions, for example a small time step indicates a more frequent delivery of control signal to the EVs, and vice versa. However, the effectiveness of the proposed model is not affected by this interval. In this control model, 6 min time step duration is considered and thus every day is consisted of 240 time steps.

In the proposed control scheme, there are four main procedures which are repeated sequentially in a daily or a time step basis (see Figure 5.4). At the beginning of each day, forecasting actions are taking place in order to estimate the future demand from the “Unresponsive” EVs.

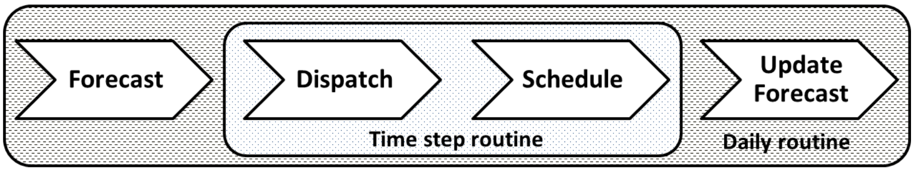

Figure 5.4: Daily and time step routine in the control model

The selected data mining method used in the EVs load forecast model is SVMs due to its high performance and its ability to extract information behind difficult patterns. Figure 5.5 presents the flowchart of the EVs load forecast model.

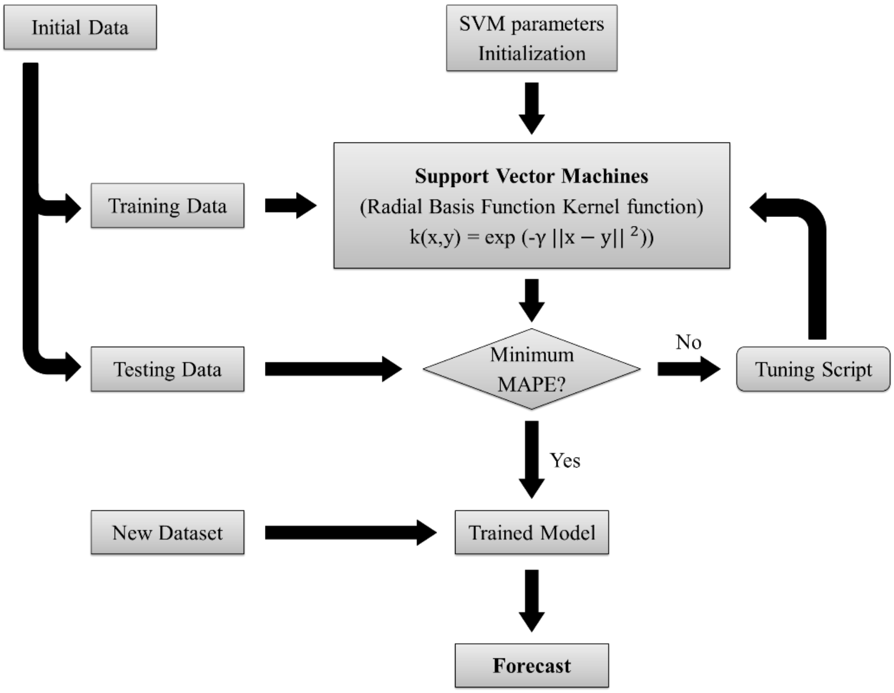

Figure 5.5: EVs load forecast model for "Unresponsive" EVs

The EVs load forecast model is updated at the end of each day with all recorded charging events. The charging data include information about the connection times, disconnection times and the energy requirement of the EVs fleet. In addition, each EVs has an ID and this is used to identify the charging pattern of a EVs owner. In addition, information about the ID of the EVs and its responsiveness to control signals is provided to the forecasting model. Based on the available information, the attributes used for the training and testing procedures are shown in Table 5-1.

Table 5-1: Attribute used for the training process

Attribute Name	**Description**
Two-day "Unresponsive" EVs Load	The aggregated charging demand from "Unresponsive" EVs of the previous two days for each time step.
Two-day "Responsive" EVs Load	The aggregated charging demand from "Responsive" EVs of the previous two days for each time step.
Two-day "Unresponsive" EVs Load of previous week	The "Unresponsive" EVs charging demand of the same days of previous week for each time step.
Two-day "Responsive" EVs Load of previous week	The "Responsive" EVs charging demand of the same days of previous week for each time step.
Day	The number of the day (1-7) starting with Monday.
Month	The number of the month (1-12) starting with January.
6 minutes' time step	1-240 parts of each day.
Number of "Unresponsive" EVs Connections	The number of "Unresponsive" EVs connections for every time step.
Number of "Responsive" EVs Connections	The number of "Responsive" EVs connections for every time step.
Number of "Unresponsive" EVs Disconnections	The number of "Unresponsive" EVs disconnections for every time step.
Number of "Responsive" EVs Disconnections	The number of "Responsive" EVs disconnections for every time step.

The target for the EVs forecast model is to forecast the EVs demand from "Unresponsive" EVs for each time step of the next two days. Once the training data are properly formed, the SVM and the RBF kernel parameters are initialised randomly. A script is executed in order to divide the sample in two separate datasets, one for the training and the other for the evaluation of the model. The testing dataset includes the values of the last two days of the initial datasets while the rest constitute the training dataset. Once the model is trained with the initial SVM parameters, it is evaluated through the testing dataset. The MAPE is calculated based on Eq. (4.2). The model is using a second script for updating the SVM parameters. The parameter C takes all integer values between the minimum and the maximum target value [83]. Additionally, parameter γ is updated within a range of $[0.85/n, 1.15/n]$ with a step of $(0.1/n)$, where n is the number of the attributes. The parameter ε is considered constant 0.001 (default value). All possible combinations of C and γ within the specified range are checked and the ones which result in the minimum MAPE are selected. Once this process is completed, the model is tested on the new dataset (which contains the attributes of the next two days) in order to provide a forecast of the charging demand from "Unresponsive" EVs for the next two days. The accuracy of this process is significant to the effectiveness of the control model.

In every time step, two main procedures are taking place namely "Dispatch" and "Schedule". The "Dispatch" procedure is presented in Figure 5.6.

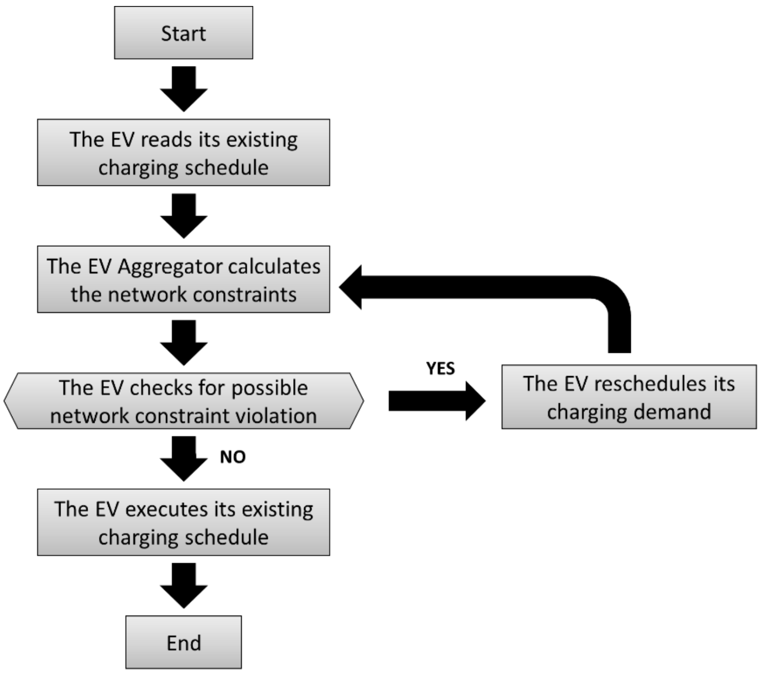

Figure 5.6: Flowchart of the Dispatch process

Every process involves different tasks from both the EVs aggregator and the corresponding EVs. The "Dispatch" procedure involves the execution of the existing EVs charging schedules. In this procedure, the EVs aggregator first runs power flows for the specific part of the distribution network according to the EVs scheduled charging demand. According to this scheduled demand, the total non EVs demand and the demand from the "Unresponsive" EVs, the real time network constraints are calculated by the aggregator and sent to the corresponding EVs. After receiving these constraints, the EVs checks for a possible violation of the network constraints. In case the limits are violated, the EVs is rescheduling this charging demand in future time steps. This procedure is repeated until the scheduled demand of every existing EVs is either supplied or rescheduled.

In case new EVs are connected (or the existing charging schedule violates the technical constraints of the network) the "Schedule" phase is activated (see Figure 5.7). During this phase, each EVs will solve the scheduling problem to satisfy its charging requirements. Internal information such as the battery SOC and the charging station power rate, as well as information coming from the EVs aggregator (external) like the network's capacity and the forecasted EVs demand are used in the scheduling process.

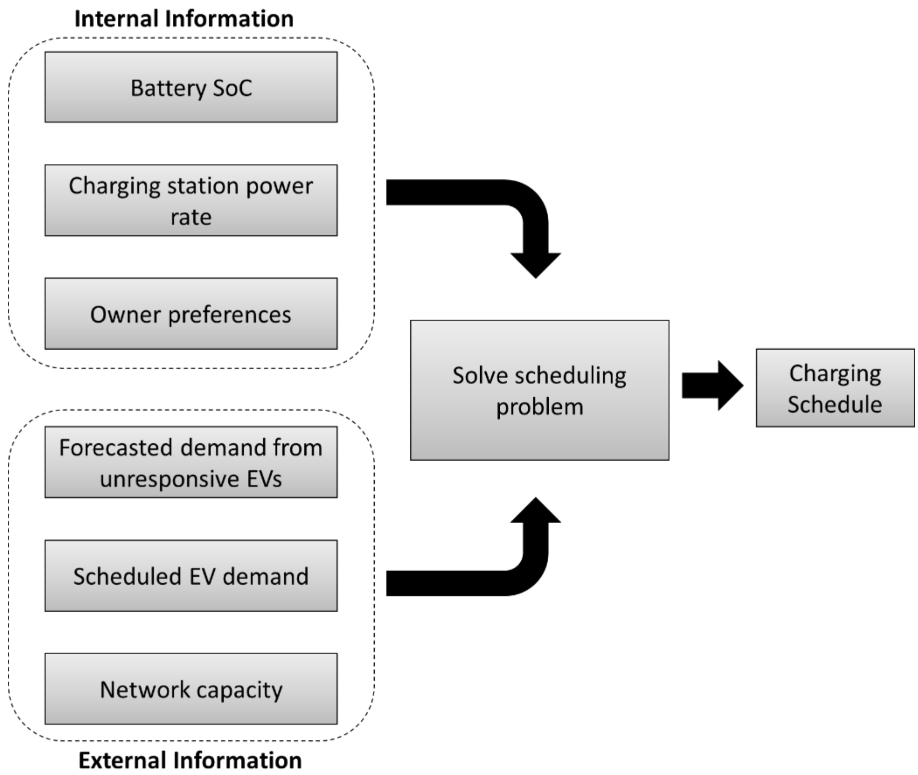

Figure 5.7: Flowchart of the Schedule process

The scheduling problem for EVs-n is formulated as follows:

$$\min \sum_{t_n}^{t_n+d_n} P_n(t) \cdot [V_n(t)] \qquad (5.1)$$

where t_n is the connection time of EVs-n, d_n is the charging duration of EVs-n , $P_n(t)$ is the instantaneous charging power demand of EVs-n and $V_n(t)$ is the virtual cost value of a time step.

Every EVs tries to minimise a virtual cost function given in Eq. (5.1). The virtual cost values $V_n(t)$ are calculated by the EVs Aggregator according to the forecasted demand from "Unresponsive" EVs, the existing EVs charging schedules and the non EVs demand. The EVs aggregator sends to every EVs a vector V_n. This vector contains the order sequence of the time steps with the lowest to highest demand for the period [t_n, t_n+d_n]. For example, the virtual cost value for the time step with the lowest demand is 1, while the one with the highest demand is d_n , and the intermediate time steps are taking values between 1 and d_n .

Minimising Eq. (5.1) will result in an adaptive EVs behaviour based on the local network's condition. Each EVs has knowledge of the future local aggregated demand and adjusts its charging schedule accordingly. The scheduling problem is subject to the following constraints:

$$\int_{t_n}^{t_n+d_n} P_n(t)dt = \left(SOC_{final_n} - SOC_{in_n}\right)\frac{C_{bat_n}}{\delta_{eff_n}} \quad (5.2)$$

$$P_n(t) \leq P_{ch.nom_n} \quad (5.3)$$

$$\forall n \in (1 \ldots N), \forall t$$

where SOC_{final_n} is the desired SOC of EVs-n, SOC_{in_n} is the initial SOC of EVs-n, C_{bat_n} is the battery capacity of EVs-n, δ_{eff_n} is the efficiency of the charging station and $P_{ch.nom_n}$ is the nominal power rate of the charging station.

Eq. (5.2) expresses the energy requirements of EVs-n. These requirements are satisfied during the connection period of the particular EVs $[t_n, t_n+d_n]$. The instantaneous charging power $P_n(t)$ must not exceed the power rating of the charging station ($P_{ch.nom_n}$) for every t, as described in Eq. (5.3). The next two constraints are related to the network topology and characteristics. Let us denote f as the LV feeder that a EVs is connected. Every such feeder has a group A_f that is consisted of all EVs charging on LV feeder f at time t. Based on the network topology, the size of this group ($|A|$) has an upper boundary C_1 (maximum number of EVs on feeder f). Additionally, denoting l as the MV/LV transformer that LV feeder f is attached, there is a group B_l $\mathrm{B_l}$containing all the corresponding feeders. C_2 expresses the number of feeders on a transformer. Eqs. (5.4) and (5.5) are used to keep the power demand of feeder f and the transformer l between the limits.

$$P_n(t) \leq P_{fd.nom_f} - \sum_m P_m(t) \quad (5.4)$$

$\forall f \exists A_f$ = {n | connected on f = true}, $|A| \leq C_1$

$$\forall m \in A_f - \{n\}$$

$$\forall n \in (1 \ldots N), \forall t$$

where $P_{fd.nom_f}$ is the nominal power of feeder f and $P_m(t)$ is the power demand of EVs-m in feeder f. Eq. (5.4) expresses that the charging power for EVs-n should not exceed the corresponding nominal feeder limit considering also all the other EVs which are charging in the same feeder.

$$P_n(t) \leq P_{tr.nom_l} - \sum_f \sum_m P_m(t) \qquad (5.5)$$

$\forall l \exists B_l = \{f \mid \text{connected on } l = \text{true}\}$, $|B|=C_2$

$\forall f \in B_l$

$\forall m \in A_f - \{n\}$

$\forall n \in (1 \ldots N), \forall t$

where $P_{tr.nom_l}$ is the nominal power limit of the transformer. Eq. (5.5) expresses that the charging power for EVs-n should not exceed the corresponding nominal transformer limit considering also all the other EVs which are charging in the same transformer.

5.4 SIMULATION RESULTS

In order to demonstrate the importance of the EVs load forecast in the proposed control scheme, different charging scenarios and different composition of the EVs fleet were considered. A specific distribution network was used to test the performance of the control model. Different percentage of "Unresponsive" EVs were considered and the effectiveness of the control model is evaluated through case studies. In addition, the effect of the charging rate on the valley filling effect on the local demand curve is also presented.

5.4.1 Network Topology

The typical 33/11/0.4kV UK generic distribution network model is based on [102]. The system is comprised of a 33kV three-phase source, two 33/11.5kV 15MVA transformers with on-line-tap-changer and an 11kV substation with five 11kV outgoing MV feeders. Each 11kV feeder supplies eight 11/0.433kV 500kVA distributed transformers. Each MV/LV transformer has four LV feeders, and each LV feeder provides energy to 96 customers. The topology is presented in Figure 5.8.

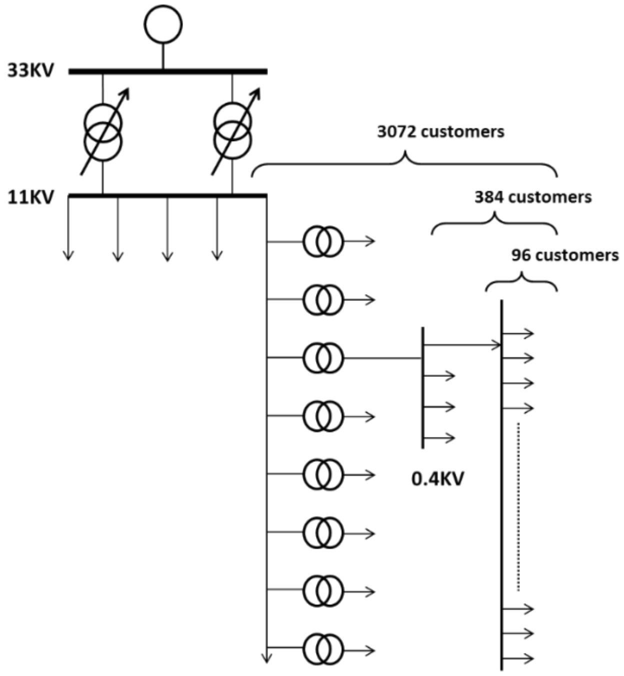

Figure 5.8: Typical 33/11/0.4 UK generic distribution network

The EVs are connected at the LV level, while the EVs aggregator is located on a MV feeder, and is responsible for 3072 customers. In order to evaluate the control model, a realistic EVs fleet with the following characteristics is created, as shown in Table 5-2.

Table 5-2: EVs Fleet characteristics

EVs Fleet variables	Mean Value (μ)	Standard Deviation (σ)
Battery Capacity (kWh)	30	2
Initial SOC (%)	40	5
Final SOC (%)	90	10
Arrival time of "Responsive" EVs (h)	09:00	1
Departure time of "Responsive" EVs (h)	17:00	1
Arrival time of "Unresponsive" EVs (h)	10:30	0.5
Departure time of "Unresponsive" EVs (h)	13:30	0.5

An uptake level of 20% EVs is considered as the Business as Usual (BAU) Scenario [42]. This uptake level was used for different case studies to investigate the impact of EVs load forecast on the effectiveness of the proposed control model. Representative charging rates of 3.6kW, 11kW and 22kW for the charging stations are considered to study their effect on the flexibility of a responsive EVs fleet. The charging stations were assumed to have a single outlet/connector and provide ac charging. Non EVs demand curves are obtained from [103] for a typical spring weekday. Different ratios of “Unresponsive” and “Responsive” EVs are used to analyse the influence of this ratio to the effectiveness of the proposed model.

5.4.2 Case Study 1

In this case study a number of 614 EVs were assumed, equivalent with 20% uptake, having the characteristics presented in Table 5-2. Different EVs fleet synthesis with “Responsive” and “Unresponsive” EVs is considered, charging at 11kW charging stations. Two control options are presented, one without activating the forecasting modules of the model, and the second one that uses the forecasting model. Figure 5.9 shows the demand on the MV level for both options (without and with EVs load forecast) for different ratios of “Responsive” and “Unresponsive” EVs.

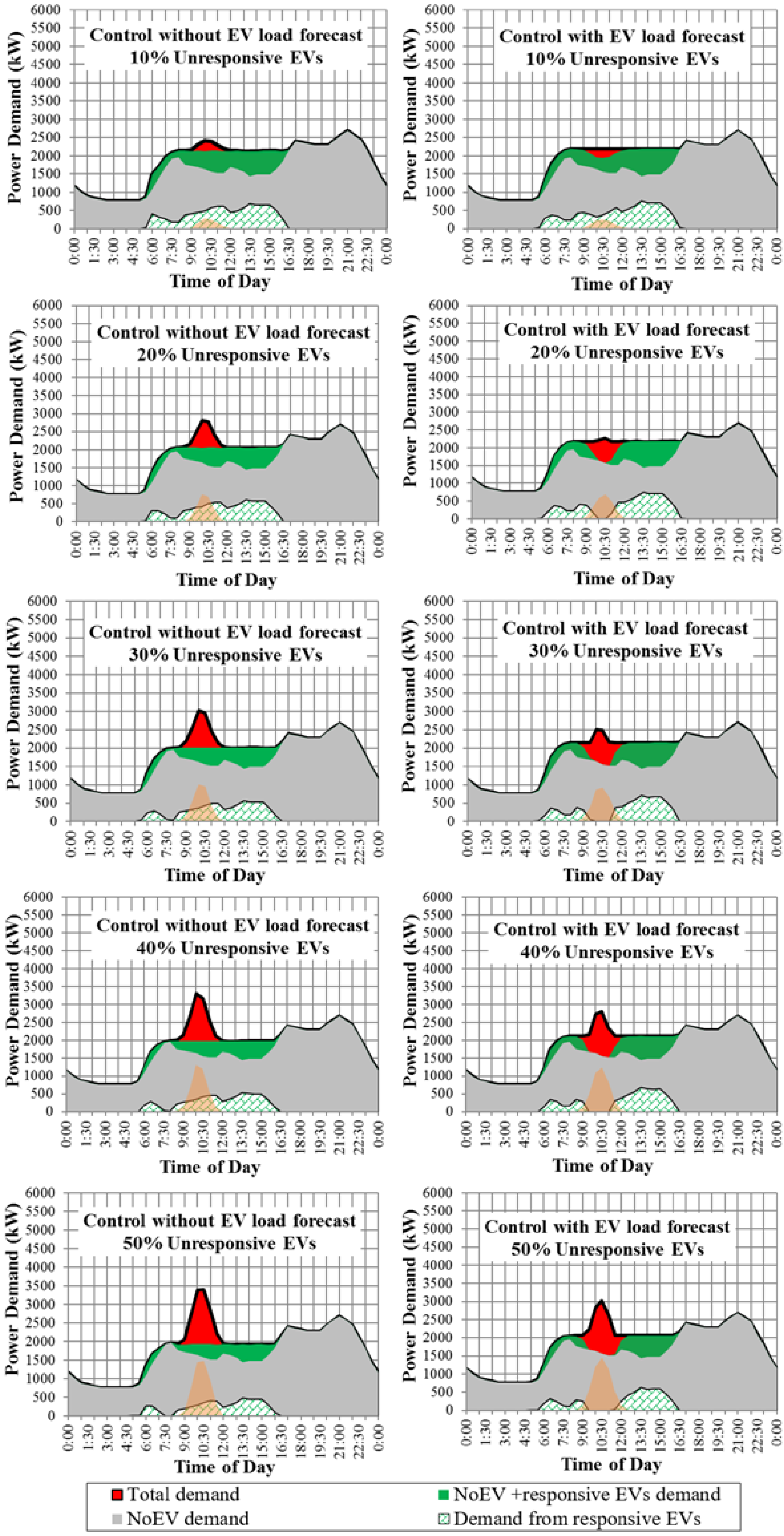

Figure 5.9: Charging demand for different levels of “Unresponsive” EVs after two control strategies

The results show that when EVs load forecast option is activated, EVs are modifying their charging schedules in order to reduce the impact of "Unresponsive" EVs charging on the demand curve. The charging demand of the "Responsive" EVs is adapted to the "Unresponsive" EVs charging demand so that their aggregation results in a valley filling effect on the Non EVs demand curve. In most cases, this adaptive behaviour of "Responsive" EVs leads to a reduction of the aggregated charging demand peak. For low levels of "Unresponsive" EVs (until 20%), the control model is able to completely absorb the "Unresponsive" EVs demand. On the other hand, high levels of "Unresponsive" EVs lead to inflexible demand, thus the capability of the proposed control model to reduce the peak charging demand is limited. Obviously, without having "Responsive" EVs in our system, the integrated model with EVs load forecast is not affecting the final charging demand.

5.4.3 Case Study 2

This case study investigates the effect of the charging stations' power rate on the effectiveness of the control model. The charging rates of 3kW, 11kW and 22kW and an uptake of 20% EVs are used for this analysis. The Peak-to-Average Ratio (*PAR*) and peak reduction criteria are used to evaluate the performance of the model. *PAR* is calculated according to Eq. (5.6). This index indicates the valley filling effect on the demand curve.

$$PAR = \frac{P_{\max}}{P_{average}} \tag{5.6}$$

where P_{max} is the peak power demand of a day and $P_{average}$ is the mean power demand for the specific day.

As seen from Figure 5.10, different charging rates have a different effect on PAR-index. At low charging rates (3.6kW) the control model with EVs load forecast is capable to delay the increase of this index, even until a 50/50 ratio of "Responsive" and "Unresponsive" EVs is achieved. For higher charging rates, "Unresponsive" EVs have a significant impact on PAR, even at low penetration levels. Despite this, the control model with EVs load forecast improves the results. At 0% and 100% levels of "Unresponsive" EVs the results are identical, and both control options lead to the same demand curve. In every combination of "Responsive" and "Unresponsive" EVs (except of course the extreme values of 0% and 100%) there is a peak reduction due to the contribution of the forecasting model. For every charging rate, this reduction can reach up to 35%. However, this reduction occurs at different percentage of "Unresponsive" EVs for each charging rate. For low charging rates a significant peak reduction is observed at a wide range of "Unresponsive" EVs percentages. On the contrary when the charging rate is increased, this range is narrower and the maximum peak reduction is found on lower "Unresponsive" EVs percentages.

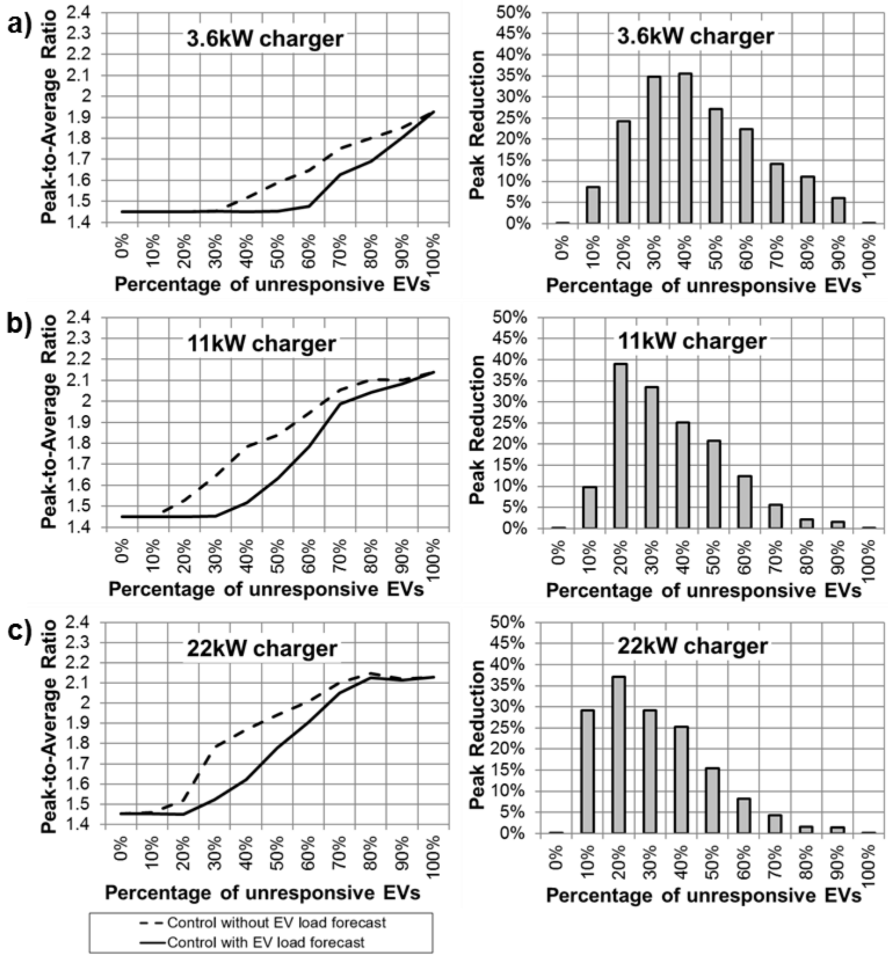

Figure 5.10: Peak-to-average ratio and Peak reduction for a) 3.6kW, b) 11kW and c) 22kW charger

5.5 SUMMARY

The flexibility of the electricity sector in managing changes will have a significant influence to the success of the electric vehicle deployment. The development of the charging infrastructure is often seen as an essential investment to offer EVs drivers the psychological support to overcome the range anxiety, one of the most inhibiting factors in EVs adoption. In order to manage the EVs charging in distribution networks, DNOs will have to upgrade their infrastructure or implement smart control techniques in parallel with the development of regulative measures to serve these new customers.

The “aggregator” is a new player which will control multiple EVs. This research is proposing a charging control framework for a mixture of “Responsive” and “Unresponsive” EVs enhanced by EVs load forecasting. The main aim of the control algorithm is to achieve a valley-filling effect on the demand curve. The effectiveness of the control algorithm was tested in a UK generic distribution network considering a geographical area with 3072 customers. Two case studies were presented. The first case study considered a EVs fleet charging at 11kW charging stations comprising of “Responsive” and “Unresponsive” EVs. It was demonstrated that when the EVs load forecast option is activated the EVs are adapting their charging schedule to reduce the impact of the “Unresponsive” EVs on the demand curve. The second case study investigated the effect of the charging station’s power rate on the effectiveness of the control model. It was shown that when the forecasting module is activated there is a demand peak reduction for every combination of “Responsive” and “Unresponsive” EVs considering charging rates of 3kW, 11kW and 22kW.

Smart management of EVs charging based on aggregation enhanced by EVs load forecasting could be seen as a win-win strategy for both the DNO and the vehicle owner.

CHAPTER 6

A MULTI-AGENT BASED SCHEDULING ALGORITHM FOR ADAPTIVE EVS CHARGING

6.1 INTRODUCTION

In this chapter a decentralised scheduling algorithm for EVs charging is presented. The charging control model follows the architecture of a MAS. Each entity was modelled as an autonomous agent, which interacts with other agents and tries to achieve its own goals. The MAS consists of a EVs/DG aggregator agent and "Responsive" or "Unresponsive" EVs agents. The EVs/DG aggregator agent is responsible to design the virtual pricing policy according to EVs charging demand and DG forecasts. "Responsive" EVs agents are the ones that respond rationally to the virtual pricing signals, whereas "Unresponsive" EVs agents define their charging schedule regardless the virtual cost. "Responsive" EVs agents are adjusting their charging schedules based on the charging demand from "Unresponsive EVs agents", indicating their adaptive behaviour. The performance of the control model was experimentally demonstrated at the EES Laboratory hosted at the NTUA. Three factors were investigated: (i) the location of the EVs/DG aggregator, (ii) the importance of forecasting the demand from "Unresponsive" EVs agents and (iii) the charging behaviour of "Responsive" EVs agents when renewables generation is available. The results showed the adaptive behaviour of "Responsive" EVs agents and proved their ability to charge preferentially from Renewables.

In contrast to the existing literature, this model considers a realistic scenario for the future EVs fleet by classifying the EVs agents into

"Responsive" and "Unresponsive" to the control strategy. To the best of my knowledge, it is the first time that the forecast of inflexible EVs charging demand is integrated in a charging control model. A novel algorithm was developed for the distributed management of EVs charging. Although the EVs agents are trying to minimise their virtual cost, this results in a valley-filling effect on the total demand curve. This is achieved through the dynamic pricing mechanism of an EVs/DG aggregator. By modifying the virtual prices after each charging request, the "Responsive" EVs agents adapt their charging demand to the demand from "Unresponsive" EVs agents.

The rest of the chapter is organised as follows. In Section 6.2 the EVs Management Framework is illustrated. The experimental demonstration of the charging control model is described in Section 6.3. A summary is given in Section 6.4.

6.2 ADAPTIVE EVS CHARGING CONTROL MODEL

6.2.1 Architecture

The EVs management scheme follows a two-layer decentralised structure based on the UK generic distribution network [102]. The bottom layer includes the EVs agents at the LV customer level, whereas the top layer includes the EVs/DG aggregator agents at the MV/LV transformer level.

The EVs/DG aggregator agent represents an energy market entity which manages the EVs charging demand and owns small scale renewable energy generation in a geographical area. It tries to increase its revenues from existing contractual agreements with the EVs owners and the DNO. The EVs/DG aggregator purchases energy from the wholesale energy market, based on forecasts for the next day's local EVs charging demand and local renewable energy generation. The EVs charging requests are operated in order to maximise the use of the local renewable energy for their charging and to minimise the purchase cost of additional energy from the grid. Ancillary services (e.g. load shifting) can also be offered to the DNOs in order to reduce the demand during the peak hours and utilise the off-peak hours for the EVs charging (valley-fill). The EVs charging demand is controlled in an indirect manner by adopting a dynamic virtual pricing mechanism according to the forecasted EVs charging demand and local renewable generation production. In the proposed pricing scheme, the EVs/DG aggregator's objective is achieved by assigning low virtual price values to the preferred hours for EVs charging, and higher virtual price values to hours where EVs charging should be avoided. Based on the charging demand, these price values are constantly updated to ensure that the objective is achieved.

The EVs agents are entities representing the EVs owner's rational behaviour. Their objective is to minimise their individual charging cost, based on the virtual price values. To this end, the EVs agents define their charging schedules individually so that they charge at the cheapest hours. As EVs are the decision making components of the charging management system, therefore the charging control model can be classified as decentralised.

Although there is not a direct interaction between them, one EVs agent's charging schedule affects the virtual price values for the other EVs agents, and thus their interdependence is indirect. In reality, it is unlikely that all EVs owners will participate in such management scheme at all times slots. The flexibility of EVs charging demand should not be taken for granted. To reflect this realistic characteristic of future EVs fleets, in the adopted charging management framework the EVs agents are classified as "Responsive" or "Unresponsive" to the pricing signals. "Responsive" EVs agents are the ones that respond rationally to the pricing signals, whereas "Unresponsive" EVs agents define their charging schedule regardless the cost.

6.2.2 Charging Control Strategy

The EV/DG aggregator provides valley-filling services to the DNO and is paid for these services. Its revenues are also increased when the charging energy demand is supplied from (owned) local renewable energy generation. In this context, the EV/DG aggregator sets a dynamic pricing strategy so that the energy demand valleys are used for the EVs charging, and when available, the owned renewable energy generation supplies the EVs charging demand.

The pricing policy considers the technical constraints of the downstream network (MV/LV transformer, LV feeders). The EV/DG aggregator prevents the violation of operational limits by modifying the virtual prices based on the network's stress level.

The "Responsive" EVs agents adjust their charging schedule to the lowest virtual prices, trying to reduce their own individual charging cost. In case of a fixed price curve, the charging demand of all the "Responsive" EVs agents would coincide during the cheapest hours, resulting in a new peak. To avoid this, the EV/DG aggregator adopts a dynamic pricing strategy where the virtual price values are updated sequentially, after the scheduling process of each "Responsive" EV agent. Figure 6.1 shows the resulting demand curve after a fixed and dynamic pricing strategy.

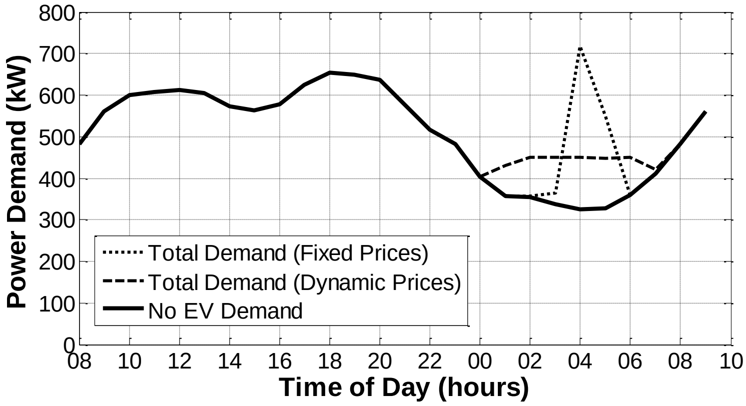

Figure 6.1: Fixed charging strategy versus Dynamic Pricing Policy Strategy

In addition, the effectiveness of the control scheme is significantly affected by the "Unresponsive" EVs agents. The inflexible charging demand from "Unresponsive" EVs agents changes the shape of the total demand curve, and is considered when setting the virtual prices, otherwise the allocation of the flexible EVs charging demand is not optimal. This effect is explained with an example. A mixture of "Responsive" and "Unresponsive" EVs agents is assumed and their arrival and departures times are shown in Figure 6.2a. An abnormal event occurs at 10:00, when a number of "Unresponsive" EVs agents connect to the charging stations requiring charging for a short period of time. Without prior knowledge of this abnormal event, the EVs/DG aggregator does not adjust the virtual prices correspondingly, and the

“Responsive” EVs agents schedule their charging in a non-optimal fashion (Figure 6.2b and Figure 6.2c). To the best of my knowledge, this example indicates the weakness of the majority of the control strategies proposed in the literature.

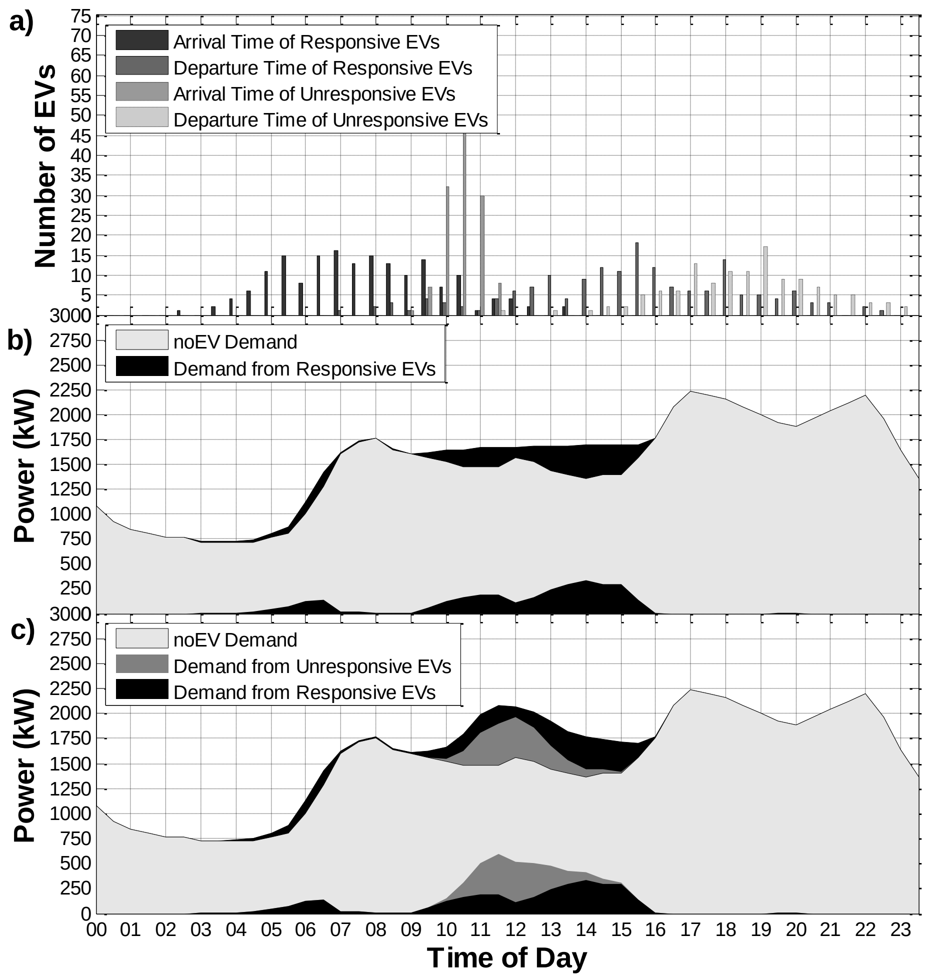

Figure 6.2: EVs Management without forecasting the demand from “Unresponsive” EVs agents

If the abnormal event is known a priori, the virtual prices could be modified to reflect the new shape of the demand curve. As a consequence of this change the “Responsive” EVs agents charge in an optimal fashion. Therefore, forecasting the demand from “Unresponsive” EVs is critical for the effectiveness of the control scheme. In the adopted control strategy, the EVs/DG aggregator forecasts the charging demand from “Unresponsive” EVs agents, and adjusts the virtual prices accordingly.

In addition, the EVs/DG aggregator tries to satisfy the EVs charging demand with the local owned renewable energy generation. To this end, it forecasts the next-day's DG and adjusts the virtual prices correspondingly. By setting lower charging cost when DGs are expected to be available, the EVs/DG aggregator incentivises the "Responsive" EVs agents to consume the DG locally. The forecast model described in Section 4.3 can be also used to produce the day ahead generation forecast scenarios. However, the DG forecasts used in Section 6.3.4 were assumed to be provided by an external source due to lack of sufficient amount of data.

The virtual price values depend on the accuracy of the forecasts (both charging demand and DG). An inaccurate forecast results in profit loss for the EVs/DG aggregator as the scheduling solution is not optimal at the end of the day. Therefore, this control strategy considers two operational modes, namely normal and emergency. During normal operation, the forecasts are accurate and the charging schedules are executed exactly as planned. In case of an error in the demand or generation forecast, an emergency mechanism is activated for the current time-step. The EVs/DG aggregator calculates the new virtual price values according to the actual demand and generation of the current time-step. The connected "Responsive" EVs agents modify their charging schedule, following the updated virtual prices. This is a sequential process, and the virtual values are updated after "rescheduling" each "Responsive" EVs agent. The emergency operation terminates when the charging demand is again optimally scheduled, based on the new condition of the system. To ensure the participation of "Responsive" EVs agents in this emergency operation, additional incentives are given (e.g. the rescheduled charging demand is not charged). This feature can be utilised to offer demand response services to DNOs, e.g. reduce the charging demand during a certain period. Additional contractual agreements should be in place, but the regulatory and contractual aspects are not in the scope of this research.

6.2.3 Charging Control Model

The charging control model follows the MAS architecture. Each entity is modelled as an autonomous agent, which interacts with other agents and tries to achieve its own goals. All the agents exist in an environment where time is measured in time-steps. During one time-step, an agent either performs a set of actions or waits for a triggering signal from another agent. A sequence of six operational phases occurs in every time-step, namely Initial, Forecasting, Planning, Normal, Emergency and Final.

In the *Initial Phase* the EVs/DG aggregator decides whether a new forecast for the demand of "Unresponsive" EVs and the renewable generation is required. The *Forecasting Phase* is executed on the first time-step of every 24 hours, and thus during *Initial Phase* the EVs/DG aggregator evaluates the current time-step. At the same time, the EVs agent compares the current time-step with its connection time-step in order to decide its next action. In case the current time-step is equal to the connection time-step the EVs agent enters its *Planning Phase*, otherwise it enters the *Normal Phase*.

During *Forecasting Phase*, the EVs/DG aggregator forecasts the two days-ahead demand of "Unresponsive" EVs and renewable generation for every LV feeder of the corresponding MV/LV transformer in a time-step resolution. The forecast model described in [104] is implemented, based on SVM and trained using historical data. The historical data contain information about the charging demand from "Unresponsive" EVs and the renewable generation profiles. Once the forecasts are available, the EVs/DG aggregator uses a typical NoEV demand profile for every LV feeder to calculate the total scheduled demand of the next day. Assuming that the day is divided in *N* time-steps, an array of *N* values was created for every LV feeder (T_{sch_DMD}). The array contains the total scheduled demand for every time-step *k*, and was calculated using Eq. (6.1):

$$T_{sch\_DMD}^{k,f} = F_{UnrespEV}^{k,f} - F_{DER}^{k,f} + S_{\mathrm{Re}spEV}^{k,f} + F_{noEV}^{k,f} \quad (6.1)$$

Where:

$k = 1 \ldots N$

$f = 1 \ldots$Number of LV feeders on MV/LV transformer.

F_{Unresp}^{k} is the forecasted charging demand from “Unresponsive” EVs for the time-step *k*.

$F_{\mathrm{Re}n}^{k}$ is the forecasted renewable generation for the time-step *k*.

$S_{\mathrm{Re}sp}^{k}$ is the total scheduled charging demand of “Responsive” EVs for the time-step *k*.

F_{noEV}^{k} is the forecasted NoEV demand for the time-step *k*.

Based on the total scheduled demand, the *N* virtual prices are calculated. A simple pricing mechanism was applied, where the virtual prices are defined in a way that they reflect the EVs/DG aggregator’s preference for EVs charging demand in a certain time-step (valley filling strategy). The EVs/DG aggregator decreases the virtual cost of charging during the time-steps with low expected demand, incentivising the EVs agents to charge accordingly. The pricing formula is presented in Eq. (6.2).

$$VP_{k,f} = \frac{T_{sch\_DMD}^{k,f}}{P_f} \cdot w \qquad (6.2)$$

Where:

P_f is the thermal power limit of the corresponding LV feeder.

w is a profit factor related to the contractual agreement between the EVs/DG aggregator and the EVs agents.

The profit factor *w* does not affect the behaviour of the model, but is related to the revenue targets of the EVs/DG aggregator. The actual contractual agreements between the EVs/DG aggregator and the EVs agents are out of the scope of this research and thus the factor *w* is assumed to be equal to 1.

In case there are new arrivals or connections of EVs agents, the agents enter in the *Planning Phase*. A queue is created (Schedule Queue) containing all the EVs agents that have just connected to their charging stations. The EVs agents of Schedule Queue solve their scheduling problem on a first-come first-served sequence based on the virtual prices sent from the EVs/DG aggregator. Therefore, the decentralised structure of the charging control model is demonstrated when each EVs agent defines its charging schedules individually. Each EVs agent solves the scheduling problem described by Eqs. (6.3) - (6.5).

$$\min \sum_{t_n}^{t_n+d_n} P_n(t) \cdot VP_{k,f}(t) \tag{6.3}$$

Subject to:

$$\int_{t_n}^{t_n+d_n} P_n(t)dt = \left(SOC_{final_n} - SOC_{in_n}\right)\frac{C_{bat_n}}{\delta_{eff_n}} \tag{6.4}$$

$$P_n(t) \le P_{ch.nom_n} \tag{6.5}$$

Where:

t_n is the connection time of EVs agent n to feeder f.

d_n is the charging duration of EVs agent n.

$P_n(t)$ is the instantaneous charging power demand of EVs agent n.

$VP_{k,f}(t)$ is the virtual cost value of each time step k .

SOC_{final_n} is the desired SOC of EVs agent n.

SOC_{in_n} is the initial SOC of EVs agent n.

C_{bat_n} is the battery capacity of EVs agent n.

δ_{eff_n} is the efficiency of the charging station.

$P_{ch.nom_n}$ is the nominal power rate of the charging station.

Eq. (6.4) expresses the energy requirements of EVs agent n. These requirements are satisfied during the connection period $[t_n, t_n+d_n]$. The instantaneous charging power $P_n(t)$ must not exceed the power rating of the charging station ($P_{ch.nom_n}$) for every t, as described in Eq. (6.5). Once the EVs agent defines its charging schedule, it informs the EVs/DG aggregator and leaves the Schedule Queue. When the EVs/DG aggregator receives a charging schedule from an EVs agent, it updates the total schedule demand T_{sch_DMD}

of the corresponding feeder. The virtual price values are recalculated according to the updated T_{sch_DMD}, waiting for the next EVs agent.

In case there are no EVs agents in the *Planning Phase*, the *Normal Phase* follows. The EVs/DG aggregator monitors the actual NoEV demand, the demand from "Unresponsive" EVs agents and the renewable energy generation for the current time-step. In order to check for possible violations of the network technical constraints, power flow analysis is performed considering the scheduled EVs charging demand (from "Responsive" EVs agents) and the monitored information (real time power demand). In case there are no violations or forecasting errors, the EVs agents execute their charging schedule for the current time-step. If the technical constraints (transformer nominal ratings, voltage statutory limits, line thermal limits) are violated or the charging schedule is not optimal due to forecasting errors, the EVs/DG aggregator transmits an emergency signal to all connected "Responsive" EVs agents. The EVs charging schedule is not executed, and the *Emergency Phase* begins.

A Reschedule Queue is created with the "Responsive" EVs agents that are connected in that time-step. The EVs/DG aggregator calculates the amount of EVs charging demand that needs to be rescheduled (P_{rsch}) in order to eliminate the problem and updates the virtual prices correspondingly. The EVs agents reschedule their charging demand for the remaining period before their departure (including the current time-step) using Eqs. (6.3)-(6.5) sequentially. After its reschedule, each EVs agent updates the total scheduled charging demand of "Responsive" EVs (S_{Resp}^{k}) and leaves the Reschedule Queue. When an EVs agent leaves the Reschedule Queue, the EVs/DG aggregator updates the Total Scheduled Demand (T_{sch_DMD}) and re-evaluates the emergency condition. If the problem remains, the P_{rsch} is recalculated along with new virtual prices, and the procedure is repeated for the next EVs agent in the Reschedule Queue. The procedure is terminated when either P_{rsch} is equal to zero, or the Reschedule Queue is empty.

During *Final Phase*, the EVs agents compare the current time-step with their departure time-step (t_n+d_n), in order to either disconnect or repeat the operation in the following time-step. At the same time, the EVs/DG aggregator returns to its initial state.

All the actions of the EVs/DG aggregator agent and the EVs agents during one time-step are presented in Figure 6.3. A sample of the MATLAB code used for scheduling EVs charging demand is presented in Appendix D.

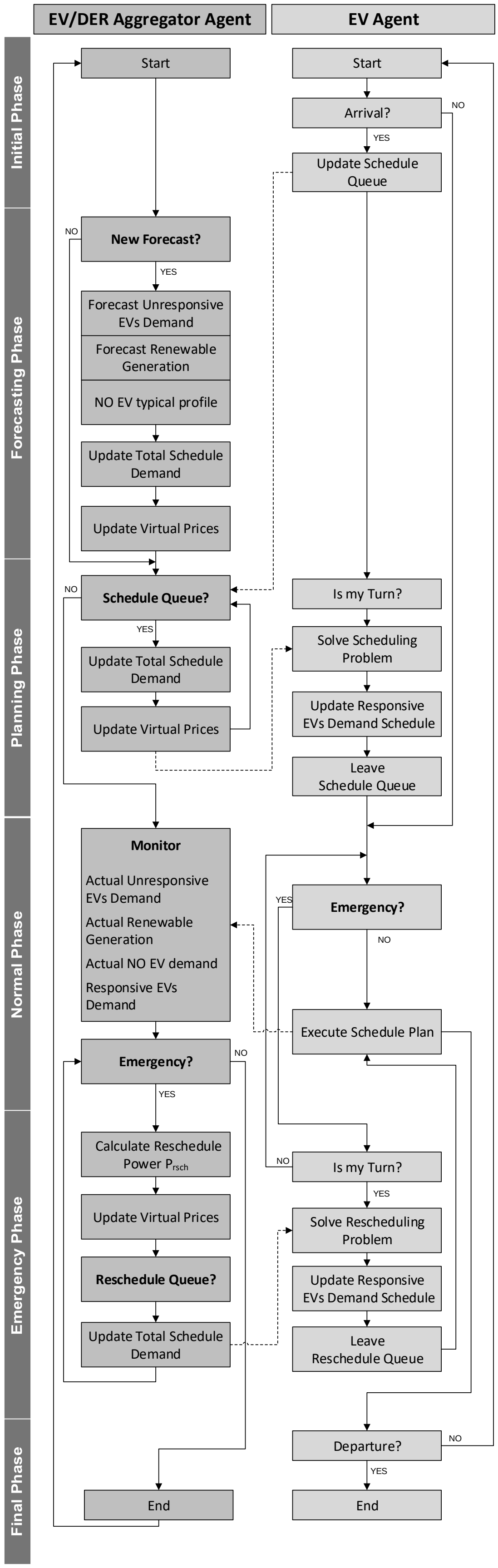

Figure 6.3: Flowchart of EVs Charging Control Model

6.3 EXPERIMENTAL RESULTS

6.3.1 General Set Up

The control model was experimentally demonstrated at the EES Laboratory hosted at the NTUA. The Model-In-the-Loop (MIL) technique is used to demonstrate the EVs charging control model under real time conditions. MIL enables the interconnection of a software model and hardware component, identifying their potential interactions and demonstrating the performance of the computer model without increased implementation costs. MIL is defined as a Hardware-in-the-Loop (HIL) testing technique with partially real and virtual (real time software program) test specimens [105]. HIL simulation is an approach where physical equipment is connected to a simulated system. This technique is used to test equipment (Hardware under Test - HuT) under real time operation conditions, approaching real life system conditions. Figure 6.4 shows a diagram depicting the MIL paradigm followed in the experiments.

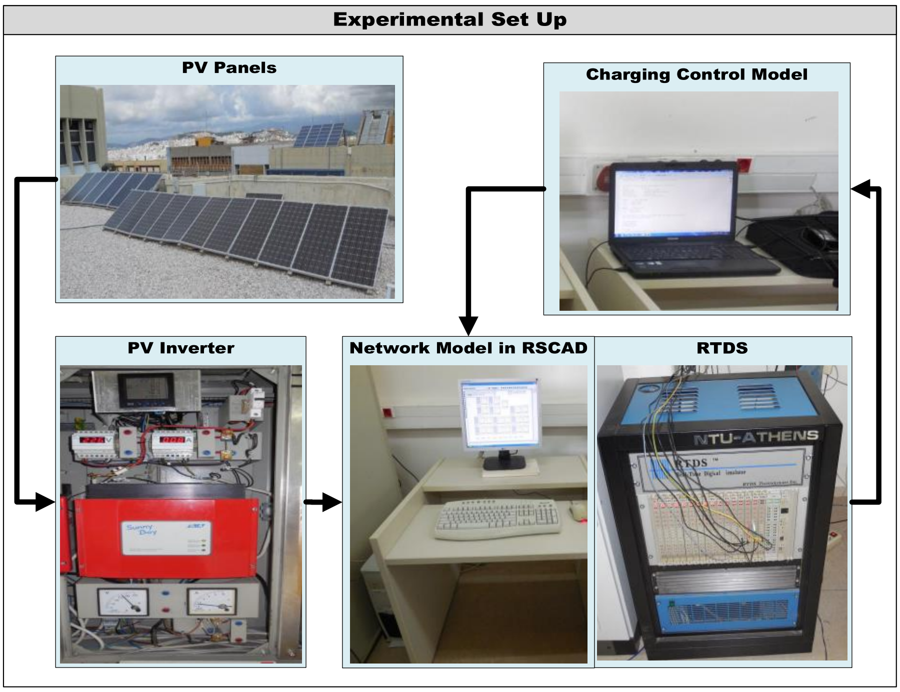

Figure 6.4: Experiment Structure

The hardware components include a Real Time Digital Simulator (RTDS) and a PV inverter whereas the charging control model is hosted on a personal computer. RTDS is a fully digital device suitable for simulating electrical power systems and networks in real time. It is used to solve power system equations fast enough to generate realistic output conditions approaching the actual operating conditions of a network. The main user's interface with the RTDS hardware is RSCAD which is used to support the design, implementation and analysis of the HIL test. The RTDS used in this setup, comprises several processing cards operating in parallel as well as various digital and analogue inputs and outputs so as to interact with the charging control model in a time step of 0.5sec.

The typical 33/11/0.4kV UK generic distribution network model [102] was simulated in RSCAD. The system is comprised of a 33kV three-phase source, two 33/11.5kV 15MVA transformers with on-line-tap-changer and an 11kV substation with five 11kV outgoing MV feeders. Each 11kV feeder supplies eight 11/0.433kV 500kVA distributed transformers with off-line-tap-changer. Each MV/LV transformer has 4 LV feeders, and each LV feeder provides energy to 96 customers. The network's topology is shown in Figure 5.8. Real-time PV generation values were obtained from 10 PV modules (110W each) through the SMA Sunny Boy inverter (1100W) and were used as inputs to the charging control model.

Three case studies were considered to demonstrate the performance of the charging control model under different operating conditions. The experiments allowed the examination of the closed-loop system consisted of the PVs, the simulated electric power network and the charging control model.

6.3.2 Locating the EVs/DG Aggregator Agent

This case study investigates the impact of EVs charging on the UK distribution network considering two different locations for the EVs/DG Aggregator. In the proposed control strategy, the EVs/DG aggregator was located at the MV/LV transformer, responsible for 384 customers equally allocated to 4 LV feeders. In this case, the virtual prices were calculated according to the demand of each LV feeder. An alternative location was also studied, where the EVs/DG aggregator was located before the MV feeder, responsible for 3072 customers (8 MV/LV transformers). In this case, the EVs/DG aggregator calculated the virtual prices according to the demand of the MV feeder. The control strategy and the behaviour of the agents were considered the same; the only difference between the two cases was the location of the EVs/DG aggregator and the calculation of the pricing signals.

The assumptions are presented in Table 6-1. In the residential charging scenario, the EVs agents are charging at home after work. An EVs uptake level of 20% is considered as the BAU scenario [42]. Therefore, a number of 640 EVs agents was considered, equally distributed to the 32 LV feeders. Non EVs demand curves were obtained from [103] for a typical Spring weekday.

Table 6-1: Fleet assumptions for the residential charging scenario

Variable	Mean Value (μ)	Standard Deviation (σ)
Number of "Responsive" EVs agents	640	-
Number of "Unresponsive" EVs agents	0	-
Arrival of "Responsive" EVs agents (h)	18:00	2
Departure of "Responsive" EVs agents (h)	08:00	2
Power of EVs charging stations (kW)	3.6	-
Efficiency of charging station (δ_{eff})	0.8	-
Battery Capacity (kWh)	30	2
Initial SOC (%)	40	10
Final SOC (%)	90	10

Figure 6.5 presents the results for the two different cases. Figure 6.5a is related to the case where the EVs/DG aggregator was located at the MV feeder. The results when the EVs/DG aggregator was located at the MV/LV transformer are shown in Figure 6.5b.

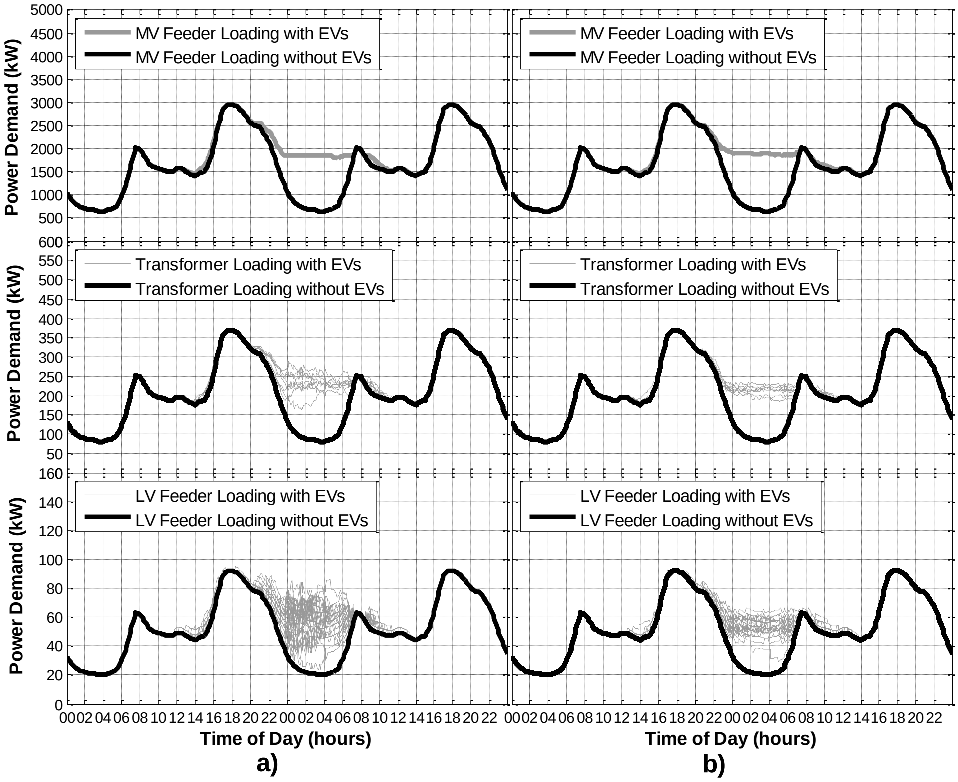

Figure 6.5: Power Demand when the location of the EV/DG aggregator agent is at the a) MV feeder b) MV/LV transformers

In both cases the EVs agents charge during off-peak hours, achieving a valley-filling effect at the demand curve of the MV feeder. However, when the prices were calculated according to the power demand of MV feeder (Figure 6.5a), the operation of the downstream network was not optimal. The demand profiles of the MV/LV transformers and the corresponding LV feeders are fluctuating during the EVs charging period. On the other hand, when the EVs/DG aggregator was located at the MV/LV transformer and the virtual prices were calculated based on the demand of each LV feeder, the demand profiles show a significant improvement. The demand fluctuation during the EVs charging period was reduced, resulting in a flattened demand curve at all voltage levels.

6.3.3 Importance of Forecasting the Charging Demand of "Unresponsive" EVs Agents

In the proposed control strategy, the EVs/DG aggregator forecasts the two days ahead charging demand of "Unresponsive" EVs agents. In this case study, the performance of the proposed control model was compared with the case when the EVs/DG aggregator does not have the capability to provide forecasts of the charging demand from “Unresponsive” EVs agents. A mixed residential EVs charging scenario was also considered in this case study. To highlight the importance of the forecasting actions, an EVs uptake level of 60% (Extreme Scenario of [42]) was considered. According to this uptake level a total number of 1,824 EVs agents was used with 352 “Unresponsive” EVs agents and 1,472 “Responsive” EVs agents. An abnormal event was assumed to occur around 21:30, when all “Unresponsive” EVs agents arrived to their charging station and start charging. A 100% accurate forecast of this event was assumed to be available, so that the EVs/DG aggregator can adjust the virtual prices accordingly. The assumptions are presented in Table 6-2.

Table 6-2: Fleet assumptions for the mixed residential charging scenario

Variable	Mean Value (μ)	Standard Deviation (σ)
Number of “Responsive” EVs agents	1472	-
Number of “Unresponsive” EVs agents	352	-
Arrival of “Responsive” EVs agents (h)	18:00	2
Departure of “Responsive” EVs agents (h)	08:00	2
Arrival of “Unresponsive” EVs agents (h)	21:30	1
Departure of “Unresponsive” EVs agents (h)	08:00	2
Power of EV charging stations (kW)	3.6	-
Efficiency of charging station (δ_{eff})	0.8	-
Battery Capacity (kWh)	30	2
Initial SOC (%)	40	10
Final SOC (%)	90	10

Figure 6.6 presents the power demand of the MV/LV transformer and its corresponding LV feeders in both cases. The results show that due to the EVs load forecasting capability of the EVs/DG aggregator, the “Responsive” EVs agents are modifying their charging schedules in order to reduce the impact of “Unresponsive” EVs charging on the demand curve. The charging demand

of the “Responsive” EVs was adapted to the “Unresponsive” EVs charging demand so that their aggregation results in a valley filling effect on the Non EVs demand curve. In most cases, this adaptive behaviour of “Responsive” EVs leads to a reduction of the aggregated charging demand peak.

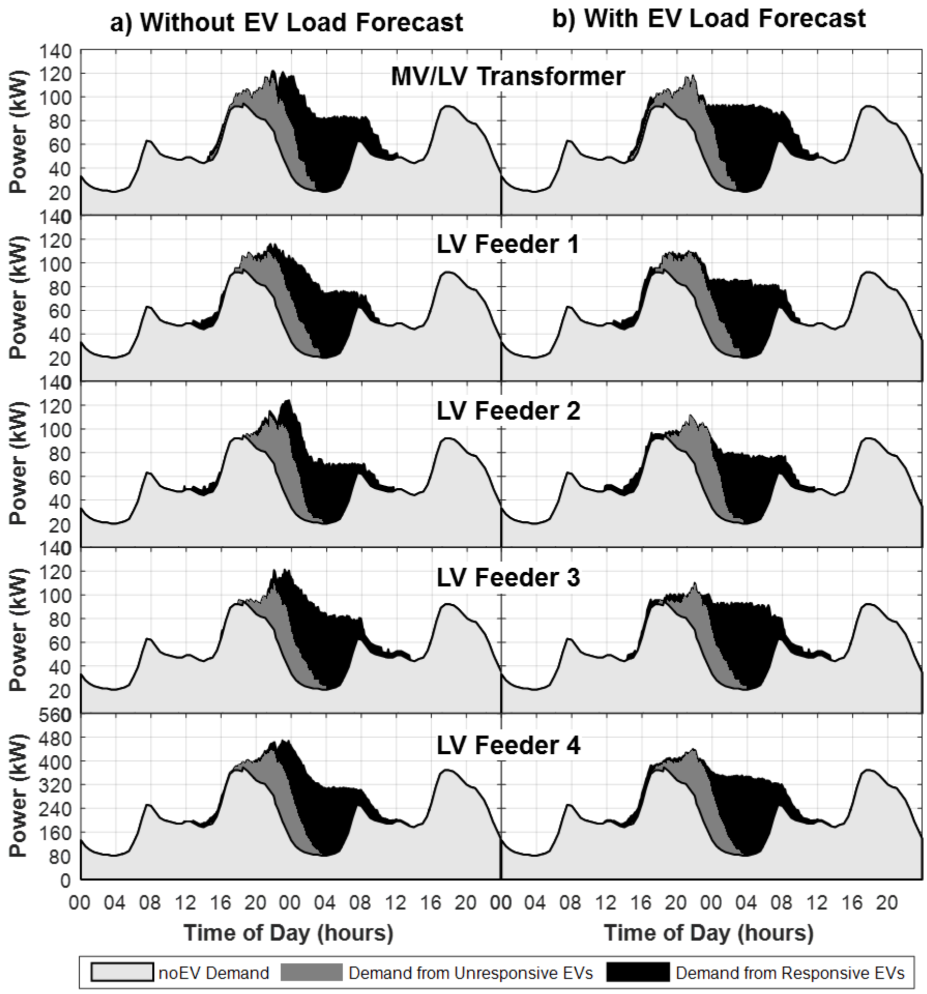

Figure 6.6: Power Demand for the MV/LV transformer and the corresponding LV feeders when the forecasting capability of the EV/DG aggregator agent is a) disabled b) enabled

The level of this reduction was affected by the charging scenario. High levels of “Unresponsive” EVs lead to inflexible demand, thus the capability of the proposed control model to reduce the peak charging demand was limited. Moreover, the accuracy of the forecast affects the final result, as the virtual prices would then be calculated based on incorrect estimation of the power demand. Finally, if the charging times of “Responsive” and “Unresponsive” EVs agents do not coincide (e.g. the responsible EVs agents charge at night and the “Unresponsive” EVs agents charge during the morning), the aggregated charging demand cannot be modified.

6.3.4 Charge Preferentially from Renewables

This case study investigates the capability of both “Responsive” and “Unresponsive” EVs agents to adapt their charging schedules to the local DG. The PV panels of the micro grid Laboratory of NTUA were used as local DG connected to one MV/LV transformer. Their capacity of 1.1kW was scaled up to 132kW in order to represent a PV park of considerable size. Historical data of one year were used to forecast the two days ahead PV generation. A morning charging scenario was assumed, where the EVs agents charge during the day. The EVs/DG aggregator agent acquired real time PV generation values from the PV inverter, and when necessary entered in the *Emergency Phase*. During this phase, the “Responsive” EVs agents modified their charging schedule, in order to consume the local DG. Table 6-3 presents the assumptions for this case study.

Table 6-3: Fleet assumptions for the morning charging scenario

Variable	**Mean Value (μ)**	**Standard Deviation (σ)**
Number of EVs agents	640	-
Arrival time of EVs agents (h)	08:00	2
Departure time of EVs agents (h)	17:00	2
Power of EVs charging stations (kW)	3.6	-
Efficiency of charging station (δeff)	0.8	-
Battery Capacity (kWh)	30	2
Initial SOC (%)	40	10
Final SOC (%)	90	10
PV generation capacity (kW)	132	-

Figure 6.7a and Figure 6.7b presents the MV/LV transformer loading and voltage of LV bus in two different cases. In the case where PVs and “Unresponsive” EVs agents were considered, a new peak was created on the

power demand curve of the MV/LV transformer. However, in the case where PVs and “Responsive” EVs agents were considered, the fluctuation in the power demand curve of the MV/LV transformer was decreased without creating a new peak. Similarly, the LV bus voltage shows less fluctuation when the “Responsive” EVs agents adapt their charging demand according to the PV generation profile.

Figure 6.7c and Figure 6.7d shows the proportion of the consumed PV generation for EVs charging from “Unresponsive” and “Responsive” EVs agents respectively. In Figure 6.7c, the 64.73% of the PV generation was used to charge the batteries of the “Unresponsive” EVs agents. However, when the EVs agents were responsive, they adjusted their charging schedules according to the times with high PV generation, utilising the 94.41% of the PV generation.

In the case with “Unresponsive” EVs agents, the proportion of their charging demand in the PV generation was depended on the charging scenario. For example, while the EVs charging demand coincides with the PV generation, this proportion increases. Therefore, unless a coincidence between EVs charging demand from “Unresponsive” EVs agents and renewable generation exists, they charge without considering the times with renewable generation.

As seen from Figure 6.7c, an unexpected drop in the PV generation occurred at around 12:00 due to cloudiness, and the EVs agents had to charge using energy from the grid. The “Unresponsive” EVs agents ignored this change and used the energy from the grid for their charging. However, this drop in the PV generation was dealt differently by the “Responsive” EVs agents. Incentivised by the EVs/DG aggregator, they entered the *Emergency Phase* and rescheduled their charging demand in a way that the required energy from the grid was consumed in a valley-filling fashion. The results demonstrated the adaptive behaviour of “Responsive” EVs agents and their preference to charge from RES.

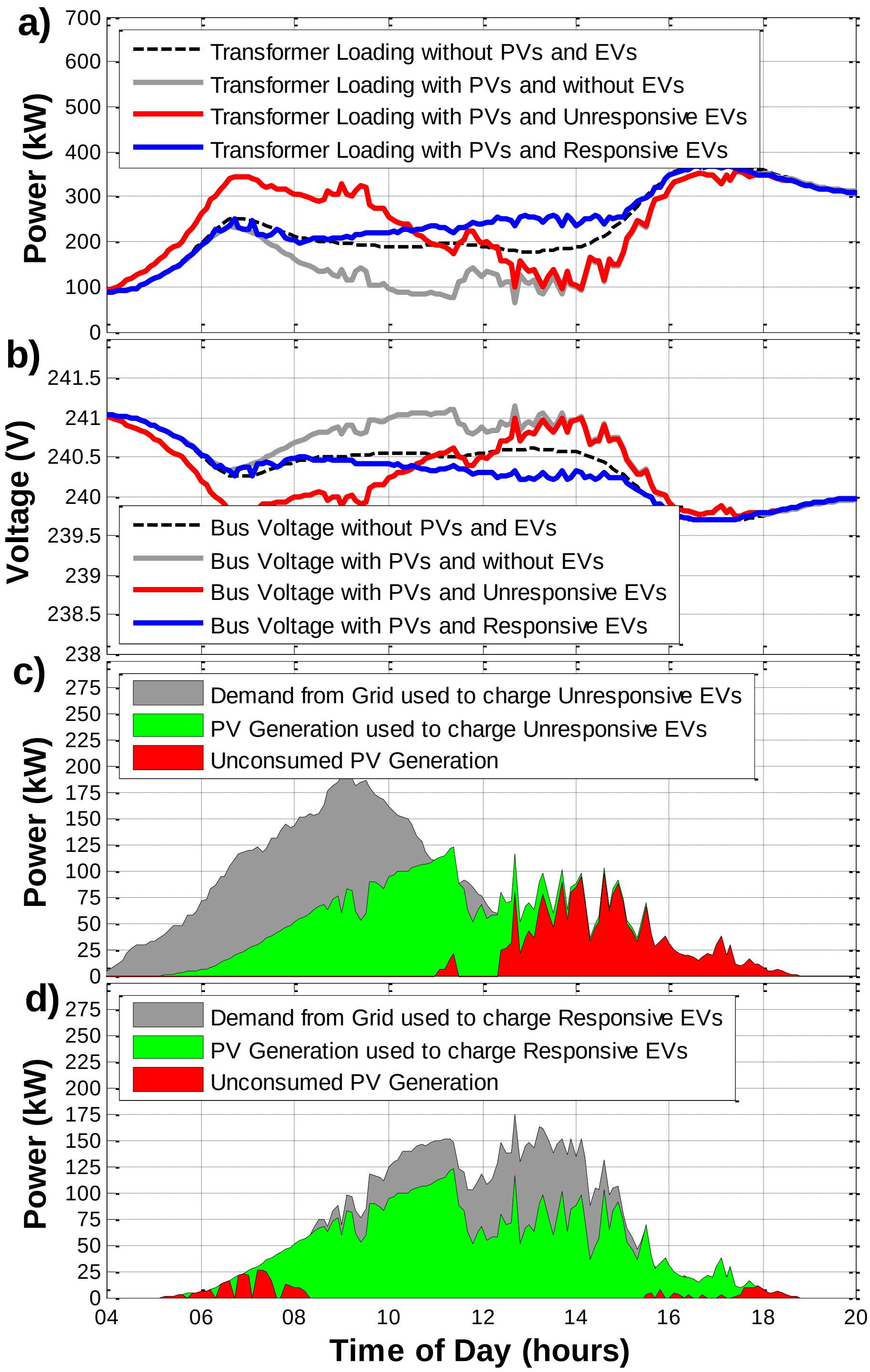

Figure 6.7: a) Power Demand for the MV/LV transformer, b) Voltage Profile at the LV bus level, c) Charging Demand from "Unresponsive" EVs agents, d) Charging Demand from "Responsive" EVs agents

6.4 SUMMARY

This research presented a decentralised EVs management framework for the EVs charging. The architecture followed in this charging control model was based on MAS. Each entity was modelled as an autonomous agent, interacting with other agents and trying to achieve its own goals. The MAS consisted of an EVs/DG aggregator agent and "Responsive" or "Unresponsive" EVs agents. The EVs/DG aggregator agent was responsible to design the appropriate virtual pricing policy so that it can achieve its objectives. "Responsive" EVs agents were able to respond rationally to the virtual pricing signals, whereas "Unresponsive" EVs agents were defining their charging schedule regardless the virtual cost.

The effectiveness of the control model was experimentally validated into the EES Laboratory of the NTUA. Three cases studies were presented. The first case study investigated the impact of EVs charging on the UK distribution network when the EVs/DG Aggregator was located either in the MV/LV transformer or the MV feeder. It was demonstrated that the location of the EVs/DG aggregator agent affects the demand and voltage profiles of the LV feeders. The second case study demonstrated the value of the EVs load forecasting in the control strategy. When the EVs/DG aggregator has load forecasting capabilities, the "Responsive" EVs agents are adapting their charging schedule to reduce the impact of the "Unresponsive" EVs agents on the demand curve. The third case study tested the capability of "Responsive" EVs agents to charge preferentially from RES. The results demonstrated their capability to reschedule their charging demand following a real time PV generation profile.

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

7.1 MAIN THESIS CONTRIBUTIONS

This thesis investigated the management of EVs charging in distribution networks. The main contributions of this thesis are summarised below:

i. A data analysis framework for handling real EVs charging data is proposed.
ii. Forecasting models for an EVs aggregator were developed.
iii. A control algorithm to manage EVs charging demand utilising forecasting processes was presented. The performance of the charging control model was demonstrated through simulation and experimental case studies.

7.2 DATA ANALYSIS FRAMEWORK FOR HANDLING REAL EVS CHARGING DATA

A data driven framework for characterising the risk level of the charging demand of EVs was presented. A data mining model was developed to extract information hidden behind charging events and to identify the characteristics of the EVs charging load. Three key characteristics of EVs charging demand in a geographical area were investigated using the proposed methodology, namely shape of the typical daily profile, predictability with respect to weather and trend of EVs charging demand. Clustering, correlation and regression analysis were performed to study each characteristic, using factors to quantify them. Analysing these characteristics resulted in assessing the potential risks and uncertainties which affect the mid-term normal operation of the corresponding distribution network. A fuzzy logic decision model was developed that aggregates the three factors into one "risk level" index. The "risk level" index was defined in order to characterise the EVs charging demand, reflecting its potential impact on the energy demand in a geographical area. The framework was applied on a dataset of real charging events from the counties of Nottinghamshire, Leicestershire and West Midlands in UK, and their "risk level" index was calculated.

The main conclusions are presented below:

i. Areas with high "risk level" values imply a potential risk for the mid-term normal operation of the distribution networks and such analysis could be important for the DNO.
ii. It was found that the EVs charging demand in West Midlands has the lowest value for "risk level" index whereas Leicestershire and Nottinghamshire on the other hand were characterised with higher values of the risk level index.

7.3 FORECASTING MODELS FOR THE EVS AGGREGATOR

An EVs Aggregator can manage the EVs charging demand more effectively if future knowledge of the system is provided. To this end, two forecasting models were developed in order to enhance the performance of the EVs charging management.

This performance is affected by various uncertainties which are associated with the random EVs charging demand patterns and the fluctuating energy market prices. The volatilities in the energy market prices are caused by large penetrations of variable renewable energy generation and random load demand. In particular, uncertainties on power generation increases with higher share of intermittent RES in the generation mix such as wind power. These uncertainties could pose technical and financial risks to EV aggregators' operation. Therefore, two methodologies were developed to forecast the future EVs charging demand as well as the available renewable generation in order to effectively coordinate EVs charging.

The first is a model for forecasting the EVs charging demand using data mining methods for the training processes. Its performance was evaluated using four different data mining method and EVs charging data from real world pilots. The key findings with regards to this model are summarised below:

i. The results showed that SVM provided the most accurate forecasts in both case studies, achieving a MAPE of less than 5%.
ii. The results showed that the training time increases significantly when using SVM compared to the other methods. Selecting the best method is a trade of between accuracy and training time.

The latter is a model for producing stochastic forecast scenarios using historical time series data for the training process. Using a rolling forecasting approach, the impact of frequent updating of the forecasts was investigated. This rolling scenarios forecasting model is updated on a regular basis, increasing its accuracy. A case study was presented to evaluate the performance of the model based on real time series data from wind generators in UK. The most significant findings with regards to this model are listed below:

i. The impact of more frequents updates on the accuracy of the model was quantified. The MAPE ranged between 32.79% - 172.08% when the base values were updated every 48 time steps. When the update frequency was increased to every 2 time steps, the range of the MAPE was between 4.9% - 14.25%; an average of 84.827% improvement.
ii. The impact of the number of magnitude intervals on the performance of the scenarios forecasting model was evaluated. For 10 magnitude classes and update frequency of 2 half-hours the error range was 23.48% whereas for 100 magnitude classes the error range was 7.96%, a reduction of 33.9%.

7.4 EVS CHARGING MANAGEMENT

A decentralised charging control model was developed following the architecture of a MAS. Each entity was modelled as an autonomous agent, which interacts with other agents and tries to achieve its own goals. The main aim of the control algorithm was to achieve a valley-filling effect on the demand curve.

The MAS consists of a EVs/DG aggregator agent and "Responsive" or "Unresponsive" EVs agents. The EVs/DG aggregator agent designs the appropriate virtual pricing policy based on accurate power demand and generation forecasts. "Responsive" EVs agents are the ones that respond rationally to the virtual pricing signals, whereas "Unresponsive" EVs agents define their charging schedule regardless the virtual cost. "Responsive" EVs agents are adjusting their charging schedules according to the charging demand from "Unresponsive EVs agents", indicating their adaptive behaviour. The performance of the charging control model was evaluated through simulation and experimental case studies.

The most significant key findings from the simulation case studies are presented below:

i. The impact of the ratio between "Unresponsive" and "Responsive" EVs on the adaptive behaviour of the "Responsive" EVs was investigated. It was demonstrated that the control model was able to completely absorb the "Unresponsive" EVs demand for low levels of "Unresponsive" EVs (up to 20%).

ii. The impact of the charging stations' power rates on the effectiveness of the control model was analysed considering different percentages of "Responsive" and "Unresponsive" EVs. It was demonstrated that the control model using demand forecasts from "Unresponsive" EVs, achieved a peak reduction up to 35% from the total load demand for every charging rate. A significant peak reduction was observed at a wide range of "Unresponsive" EVs percentages for low charging rates. However, when the charging rate was increased, this range was narrower and the maximum peak reduction was found on lower percentages of "Unresponsive" EVs.

The control model was experimentally demonstrated at the EES Laboratory hosted at the NTUA. The Model-In-the-Loop (MIL) technique is used to demonstrate the EVs charging control model under real time conditions. The hardware components included RTDS and PV inverter whereas the charging control model was hosted on a personal computer.

The most significant key findings from the experimental cased studies are concluded below:

i. The effect of the location of the EVs/DG aggregator on the performance of the control model was investigated. An improved operation of the network was indicated when the EVs/DG aggregator is located at the MV/LV transformers in contrast to when the EVs/DG aggregator is located at the MV feeder level. It was demonstrated that the demand fluctuation during the EVs charging period was reduced, resulting in a flattened demand curve at all voltage levels.
ii. The performance of the proposed control model was compared with the case when the EVs/DG aggregator does not have the capability to provide forecasts of the charging demand from "Unresponsive" EVs agents. The experiments demonstrated that the charging demand of the "Responsive" EVs was adapted to the "Unresponsive" EVs charging demand so that their aggregation resulted in a valley filling effect on the non EVs demand curve.
iii. The capability of both "Responsive" and "Unresponsive" EVs agents to adapt their charging schedules to the local DG was investigated. It was demonstrated that "Responsive" EVs agents adjusted their charging schedules according to the times with high PV generation, utilising the 94.41% of the PV generation.

7.5 FUTURE WORK

The work presented in this thesis can be extended in the following ways:

i. The appropriateness of various different communication technologies like Power Line Communication (PLC), Digital Subscriber Line (DSL), General Packet Radio Service (GPRS), Wi-Fi, etc for the agents' interactions within the MAS could be investigated. The communication infrastructure must be reliable and secure with low latencies for the normal exchange of messages among the agents. The number of messages needed for the coordination of EVs will define the specifications for the necessary communication systems.

ii. In this work, the power rate of EVs battery charging was assumed to be constant and independent to the battery SOC. In reality, the charging power rate of a battery is dependent on the SOC and voltage of the battery [27]. The battery degradation accelerates with high charging current, temperature, SOC and DOD. The impact of the charging control model on the EVs battery SOH could be examined.

iii. The V2G capability could be incorporated in the charging control model. The adaptive behaviour of "Responsive" EVs agents could be improved further if V2G capability exists.

7.6 OVERALL RESEARCH BENEFIT

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

Distribution system operators may benefit from this research in different ways. The proposed framework for analysing real EVs charging data may indicate areas with high risk level index. Therefore, this increases their awareness for the potential risk of the mid-term normal operation of the distribution networks in the corresponding area. In addition, the proposed EVs charging control model achieves a valley filling effect on the demand curve, reduces the peak demand and increases the utilisation of DG for EVs charging. These result in an optimal operation of the distribution network even with high penetrations of EVs. Therefore, this is a cost effective solution for the DSO because they may postpone expensive network reinforcement.

EVs aggregators may have various benefits from this research work. As an energy market entity, it tries to increase its revenues from existing contractual agreements with the EVs owners and the DNO. The developed algorithms for predicting and controlling EVs charging demand may help EVs Aggregators meet their contractual agreements and increase their profits.

Society and the environment may generally benefit from this research. The management of EVs battery charging could increase the utilisation of higher shares of RES, and effectively higher CO_2 emissions reductions. In addition, economic benefits may be seen due to the deferral of expensive infrastructural reinforcements of distribution networks.

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APPENDIX A

A sample of the MATLAB code used for the development of the clustering module (presented in Chapter 3) is shown below.

```
for cluster_type=2:2
    for profile=1:profiles
        All_Criterion_Values=[];
        All_IDXs=[];
        All_clusters=[];
        for evaluation_index=1:4
            if cluster_type==1
                orio=floor(size(hourly_dmd,1)/168);
                grammi=orio*168;
                demand1=reshape(hourly_dmd(1:grammi,profile),168,[])';
            else
                orio=floor(size(hourly_dmd,1)/24);
                grammi=orio*24;
                demand1=reshape(hourly_dmd(1:grammi,profile),24,[])';
            end;
            demand=[];
            for lopa1=1:size(demand1,1)
                if sum(demand1(lopa1,:))>0
                    demand=vertcat(demand,demand1(lopa1,1:end));
                end;
            end;
            max_cluster_check2=7;
            if evaluation_index==1
                Evaluation_cluster2 =
evalclusters(demand,'kmeans','CalinskiHarabasz','klist',[1:max_cluster_che
ck2]);
                index_name='Calinski';
                h=Evaluation_cluster2.CriterionValues;
            elseif evaluation_index==2
                Evaluation_cluster2 =
evalclusters(demand,'kmeans','silhouette','klist',[1:max_cluster_check2]);
                index_name='silh';
                h=Evaluation_cluster2.CriterionValues;
            elseif evaluation_index==3
                Evaluation_cluster2 =
evalclusters(demand,'kmeans','Gap','klist',[1:max_cluster_check2]);
                index_name='Gap';
                h=Evaluation_cluster2.CriterionValues;
            else
                Evaluation_cluster2 = evalclusters(demand,'kmeans',
'DaviesBouldin','klist',[1:max_cluster_check2]);
                index_name='Davies';
                h=Evaluation_cluster2.CriterionValues;
            end;
            All_Criterion_Values= [All_Criterion_Values
                h];
```

```
            clear h;
            num_cluster=Evaluation_cluster2.OptimalK;
            [IDX,Centroids] = kmeans(demand,num_cluster,..
'distance','sqEuclidean', 'Display','iter','emptyaction','drop');
            proto=min(IDX);
            teleutaio=max(IDX);
            Centroid_ID=[proto:teleutaio];
            Total_Num_of_IDXs=zeros(1,teleutaio);
            weights=zeros(1,teleutaio);
            athroisma=size(IDX,1);
            for lopa1=proto:teleutaio
                for lopa2=1:size(IDX,1)
                    if IDX(lopa2,1)==lopa1
                        Total_Num_of_IDXs(1,lopa1)=
Total_Num_of_IDXs(1,lopa1)+1;
                    end;
                end;
                weights(1,lopa1)=Total_Num_of_IDXs(1,lopa1)/athroisma;
            end;
            temp3=ones(1,teleutaio);
            temp4=evaluation_index*temp3;
            All_IDXs=[All_IDXs IDX];
clusters_results=vertcat(temp4,Centroid_ID,Total_Num_of_IDXs,weights,Centr
oids');
            All_clusters=[All_clusters clusters_results];
        end;
        final_All_IDXs=[All_IDXs demand sum(demand,2)];
        temp_cluster=All_clusters(5:end,:);
        whole_dmd=zeros(1,size(temp_cluster,2));
        for j=1:size(temp_cluster,2)
            whole_dmd(1,j)=sum(temp_cluster(:,j));
        end;
        res_dmd=zeros(1,size(temp_cluster,2));
        for j=1:size(temp_cluster,2)
            for i=1:size(temp_cluster,1)
                ora= mod(i,24);
                if ora<=7 || ora>=16
                    res_dmd(1,j)= res_dmd(1,j)+ temp_cluster(i,j);
                end;
            end;
        end;
        fuzzy_res_dmd=zeros(1,size(temp_cluster,2));
        for j=1:size(temp_cluster,2)
            if  whole_dmd(1,j)>0
                fuzzy_res_dmd(1,j)= res_dmd(1,j)/whole_dmd(1,j);
            end;
        end;
Centroids_dmd_characteristics=vertcat(whole_dmd,res_dmd,fuzzy_res_dmd);
     end;
end;
```

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APPENDIX B

A sample of the MATLAB code used in the model for forecasting electric vehicle charging demand using Support Vector Machines is described below.

```
target_train1 = demand_profile((13:end),i);
atributes_train1 = demand_profile((1:12),i);

target_test1 = target_train1;
atributes_test1 = target_train1;

c=ceil((max(demand_profile(:,i))));
g=(1/10);
phrase1='-s 3 -t 2 -g';
gamma=sprintf(' %f',g);
phrase2='-c ';
com=sprintf(' %f',c);
phrase3='-e 0.1';

options=strcat(phrase1,gamma,phrase2,com,phrase3);

model1 = libsvmtrain(target_train1, atributes_train1,… options);

[EV_Forecast] = libsvmpredict(target_test1, … atributes_test1, model1);

clear g c phrase1 gamma phrase2 com;
clear EV_Forecast target_train1 atributes_train1;
clear target_test1 atributes_test1;
clear i j phrase3 epiloges model1;
```

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APPENDIX C

The main MATLAB code used for the development of the model for producing the stochastic forecast scenarios (presented in Chapter 6) is shown below.

```
All_Steps=[11 21 51 101];
fore_Scenarios=[20 50 100 200 500 1000];
s=size(All_Steps,2);
f=size(fore_Scenarios,2);
orizontas=[48 24 16 12 8 4 2];
Days_Forecast=1;
indexes=6;
TEMP_RES=zeros(s*f*7,indexes);
Final_Res_names=cell(s*f*7,3);
clear s f;

for forecast_loop=1:1%size(fore_Scenarios,2)
forecast_loop_phrase=strcat('For_',num2str(fore_Scenarios(forecast_loop)))
;
    for StepSize_Case=1:1%size(All_Steps,2)
StepSize_Case_phrase=strcat('_Steps_',num2str(All_Steps(1,StepSize_Case)))
;
        %%%%%%%%%% input data  %%%%%%%%%%%%%
        workbookFile='WPD_kriton.xlsx';
        evdata = importfile(workbookFile);
        dmd=cell2mat(evdata(2:end,1));
        clear workbookFile evdata;
        fprintf('Start Creating Probability Density Function for %s with
%s\n',forecast_loop_phrase,StepSize_Case_phrase);
        max_power= 1+max(dmd);
        norm_dmd=dmd./max_power;
        clear dmd;
        Proto_Timestep=size(norm_dmd,1)-(Days_Forecast*48);
        train=norm_dmd(1:Proto_Timestep,1);
        test=norm_dmd(Proto_Timestep:Proto_Timestep+(Days_Forecast*48)-
1,1);
        num_Forecasts=fore_Scenarios(1,forecast_loop);
        orizontas=[48 24 16 12 8 4 2];
        Number_Steps=All_Steps(1,StepSize_Case);
        Steps = (linspace(0,1,Number_Steps))';
        for loopa1=1:1:1                %%%%%(Days_Forecast*48)
            frasi='Half_hours_forward_';
            frasi2=num2str(loopa1);
            frasi3=strcat(frasi,frasi2);
            for i=1:(size(Steps,1)-1)
                display(Steps(i,1));
                clear all_cases_increase all_cases_decrease
all_cases_flat;
                all_cases_increase=[];
```

```
                all_cases_decrease=[];
                all_cases_flat=[];

                dmd_min=Steps(i,1);
                dmd_max=Steps(i+1,1);
                temp1='Step';
                temp2=num2str(i);
                phrase=strcat(temp1,temp2);
                for loopa2=2:size(train,1)-1
                    if loopa2+loopa1<=size(train,1)
                        if train(loopa2,1)>=dmd_min &&
train(loopa2,1)<dmd_max
                            if train(loopa2-1,1)>=dmd_min && train(loopa2-
1,1)<dmd_max
                                all_cases_flat=[all_cases_flat
                                    train(loopa2+1,1)];
                            elseif train(loopa2-1,1)>=dmd_max
                                all_cases_decrease=[all_cases_decrease
                                    train(loopa2+1,1)];
                            elseif train(loopa2-1,1)<dmd_min
                                all_cases_increase=[all_cases_increase
                                    train(loopa2+1,1)];
                            else
                                display('de brika tpt');
                            end;
                        end;
                    end;
                end;
                clear loopa2;
                if size(all_cases_flat,1)>0
                    ksd_flat =
fitdist(all_cases_flat,'kernel','Kernel','triangle');
                    WInd_Past_Cases.(frasi3).(phrase).('Flat') =struct
('all_cases_flat',all_cases_flat,'Kernel_Probability',ksd_flat);
                    State_Flat=0;
                    clear ksd_flat;
                else
                    State_Flat=1;
                end;
                if size(all_cases_decrease,1)>0
                    ksd_decrease =
fitdist(all_cases_decrease,'kernel','Kernel','triangle');
                    WInd_Past_Cases.(frasi3).(phrase).('Decrease') =struct
('all_cases_Decrease',all_cases_decrease,'Kernel_Probability',ksd_decrease
);
                    clear ksd_decrease;
                    State_decrease=0;
                else
                    State_decrease=1;
                end;
                if size(all_cases_increase,1)>0
                    ksd_increase =
fitdist(all_cases_increase,'kernel','Kernel','triangle');
                    WInd_Past_Cases.(frasi3).(phrase).('Increase') =struct
('all_cases_Increase',all_cases_increase,'Kernel_Probability',ksd_increase
);
                    State_increase=0;
```

```
                    clear ksd_increase;
                else
                    State_increase=1;
                end;
                if (State_increase==1)&& (State_decrease==1)&&
(State_Flat==1)
                    fprintf('There is no KSD for the Step
%d:\n',Steps(i,1));
                end;
            end;
        end;
        clear loopa1 ;
        fprintf('End Creating Probability Density Function for %s with
%s\n',forecast_loop_phrase,StepSize_Case_phrase);
        display('Start Forecasting');
        all_Updates=size(orizontas,2);
        for periptosi=1:all_Updates
            clear Fore_Update forecast_table;
            fprintf('Update Forecast Every %d
timesteps:\n',orizontas(1,periptosi));

Update_Phrase=strcat('_Update_',num2str(orizontas(1,periptosi)));
            Fore_Update=0:orizontas(1,periptosi):(Days_Forecast*48);
            forecast_table=zeros((Days_Forecast*48),num_Forecasts);
            for MonteCarlo=1:num_Forecasts
                for timestep=0:1:(Days_Forecast*48)-1
                    ts=timestep+Proto_Timestep;
                    clear dmd_now dmd_bef state;
                    state=0;
                    if timestep<2
                        dmd_now=norm_dmd(ts,1);
                        dmd_bef=norm_dmd(ts-1,1);
                    else
                        for loopa=1:(size(Fore_Update,2)-1)
                            if timestep==Fore_Update(1,loopa)
                                dmd_now=norm_dmd(ts,1);
                                dmd_bef=norm_dmd(ts-1,1);
                                state=1;
                            end;
                        end;
                        clear loopa;
                        if state==0
                            dmd_now=forecast_table(timestep,MonteCarlo);
                            dmd_bef=forecast_table(timestep-1,MonteCarlo);
                        end;
                        clear state;
                    end;
                    clear dmd_min dmd_max temp1 temp2 phrase;
                    for i=1:(size(Steps,1)-1)
                        dmd_min=Steps(i,1);
                        dmd_max=Steps(i+1,1);
                        temp1='Step';
                        temp2=num2str(i);
                        phrase=strcat(temp1,temp2);
                        if dmd_now<dmd_max && dmd_now>=dmd_min
                            frasi='Half_hours_forward_1';
                            if dmd_bef<dmd_max && dmd_bef>=dmd_min
```

```
                                if
isfield(WInd_Past_Cases.(frasi).(phrase),'Flat')
ksd=WInd_Past_Cases.(frasi).(phrase).('Flat').('Kernel_Probability');
                                elseif
isfield(WInd_Past_Cases.(frasi).(phrase),'Increase')
ksd=WInd_Past_Cases.(frasi).(phrase).('Increase').('Kernel_Probability');
                                elseif
isfield(WInd_Past_Cases.(frasi).(phrase),'Decrease')
ksd=WInd_Past_Cases.(frasi).(phrase).('Decrease').('Kernel_Probability');
                                else
                                    display(phrase);
                                end;

                            elseif dmd_bef<dmd_min
                                if
isfield(WInd_Past_Cases.(frasi).(phrase),'Increase')

ksd=WInd_Past_Cases.(frasi).(phrase).('Increase').('Kernel_Probability');
                                elseif
isfield(WInd_Past_Cases.(frasi).(phrase),'Flat')
ksd=WInd_Past_Cases.(frasi).(phrase).('Flat').('Kernel_Probability');
                                elseif
isfield(WInd_Past_Cases.(frasi).(phrase),'Decrease')
ksd=WInd_Past_Cases.(frasi).(phrase).('Decrease').('Kernel_Probability');
                                else
                                    display(phrase);
                                end;
                            else
                                if
isfield(WInd_Past_Cases.(frasi).(phrase),'Decrease')

ksd=WInd_Past_Cases.(frasi).(phrase).('Decrease').('Kernel_Probability');
                                elseif
isfield(WInd_Past_Cases.(frasi).(phrase),'Flat')

ksd=WInd_Past_Cases.(frasi).(phrase).('Flat').('Kernel_Probability');
                                elseif
isfield(WInd_Past_Cases.(frasi).(phrase),'Increase')

ksd=WInd_Past_Cases.(frasi).(phrase).('Increase').('Kernel_Probability');
                                else
                                    display('den yparxei kamia ksd');
                                    display(phrase);
                                end;
                            end;
                            temp=abs(ksd.random(1,1));
                            forecast_table(timestep+1,MonteCarlo)=temp;
                            clear temp ksd;
                        end;
                    end;
                end;
            end;
```

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APPENDIX D

A sample of the MATLAB code used for the scheduling of EVs charging is described below.

```
% Port = 8085;
% Host ='192.168.1.114';
% % Open the connection
% JTCPOBJ = jtcp('REQUEST',Host,Port);        % Runtime is acting as TCP
socket server
%******************* Initialisation *****************************
period=2;                                   % days
customers=610;                              %number of customers
max_penetration=1;                          %max EV penetration
timeslot_duration=0.1;                      %duration
ts=24/timeslot_duration;                    %number of timeslots in 1 day

modes=[1               %residential charger
       0               %public charger
      0];              %fast charger

types=[0            %dumb charging
       1            %eco charging
       0];          %smart charging
[nom_11_04_transf, nom_LV_feeders, nom_MV_feeder, DER_F, NoEV_DMD,
id_rates]=parametroi();
[DER_Fore_ts , der_real_stili]=der_kampiles();
der_real=zeros(period*ts,32);
x=zeros(3200,(period*ts));
schedule=[id_rates x];
der_schedule=schedule;
EV_Forecast_ts=zeros(period*ts,1);
NoEV_DMD_ts=gram_paremboli(NoEV_DMD, period, timeslot_duration);
DER_Forecast_ts1=[];
DER_Forecast_ts=zeros(period*ts,1);
total_DMD=zeros(period*ts,1);
fMV_real=zeros(period*ts,1);
tr_real=zeros(period*ts,8);
fd_real=zeros(period*ts,32);
der_real=zeros(period*ts,32);
real_noev=NoEV_DMD_ts;
total_der=zeros(period*ts,32);
[fMV, t1, t2, t3, t4, t5, t6, t7, t8, f11, f12, f13, f14, f21, f22, f23,
f24, f31, f32, f33, f34, f41, f42, f43, f44, f51, f52, f53, f54, f61, f62,
f63, f64, f71, f72, f73, f74, f81, f82, f83,
f84]=availability(NoEV_DMD_ts, nom_MV_feeder, nom_LV_feeders,
nom_11_04_transf, period, timeslot_duration);
tr=[t1 t2 t3 t4 t5 t6 t7 t8];
fd=[f11 f12 f13 f14 f21 f22 f23 f24 f31 f32 f33 f34 f41 f42 f43 f44 f51
f52 f53 f54 f61 f62 f63 f64 f71 f72 f73 f74 f81 f82 f83 f84];
%********************** FLeet ********************************
```

```
[stolos]=EV_fleet(timeslot_duration, max_penetration, customers, period,
types);
stolos2=stolos;
clear customers max_penetration modes;
%*********************** Start *****************************
if types(1,1)==0
    [rank_sm] = smart_rank (ts, EV_Forecast_ts, NoEV_DMD_ts, 1, period);
end;
asdf=[];
step=timeslot_duration*10;
qwerty=[];
for day=1:(period);
    stili=(day-1)*8+1;
    c=1;                             %counter of EV arriving on k
    z=(day-1)*ts;                    %last timeslot of last day

   for i=1:ts                       %timeslot of day#
        tic;
        k = z+i;                     %real time
        kk=k+1;
        total_DMD(k,1)=real_noev(k,1);
        fMV_real(k,1)=4000-total_DMD(k,1);
        for loop=1:8
            tr_real(k,loop)=500-((total_DMD(k,1))/8);
        end;
        for loop=1:32
            fd_real(k,loop)=125-((total_DMD(k,1))/32);
        end;
        for loop=1:32
            der_real(k,loop)=der_real_stili(k,1);
        end;
%**************************** DISPATCH ***********************************
        if types(2,1)==1
            for gr=1:3200
                if der_schedule(gr,kk)>0
                    idd=der_schedule(gr,1);
                    if day>1
                        found=0;
                        for p=1:size(stolos2,1)
                            if stolos2(p,stili+1)==idd
                                evdata2=[stolos2(p,stili)
stolos2(p,stili+1) stolos2(p,stili+2) stolos2(p,stili+3)
stolos2(p,stili+4) stolos2(p,stili+5) stolos2(p,stili+6)
stolos2(p,stili+7)];
                                if evdata2(1)<k
                                    found=1;
                                    break;
                                end;
                            end;
                        end;
                        if found==0
                            for p=1:size(stolos2,1)
                                if stolos2(p,stili+1-8)==idd
                                    evdata2=[stolos2(p,stili-8)
stolos2(p,stili+1-8) stolos2(p,stili+2-8) stolos2(p,stili+3-8)
stolos2(p,stili+4-8) stolos2(p,stili+5-8) stolos2(p,stili+6-8)
stolos2(p,stili+7-8)];
```

```
                                break;
                            end;
                        end;
                    end;
                else
                    for p=1:size(stolos2,1)
                        if stolos2(p,stili+1)==idd
                            evdata2=[stolos2(p,stili)
stolos2(p,stili+1) stolos2(p,stili+2) stolos2(p,stili+3)
stolos2(p,stili+4) stolos2(p,stili+5) stolos2(p,stili+6)
stolos2(p,stili+7)];
                            break;
                        end;
                    end;
                end;

                t=floor(idd/1000);
                f=floor(mod(idd,1000)/100);
                xx=(t-1)*4+f;
                isxis_der=der_schedule(gr,kk);

                [P_der_error, der_real]=der_dispatch_function(idd, k,
isxis_der, der_real);
                total_der(k,xx)=total_der(k,xx)+isxis_der;
                if P_der_error>0.01

                    total_der(k,xx)=total_der(k,xx)-P_der_error;
                    der_schedule(gr,kk)=der_schedule(gr,kk)-
P_der_error;
                    Der_Energy_error=P_der_error*timeslot_duration;
                    cpnew=evdata2(1)+evdata2(3)-k;
                    evdata_new=[k evdata2(2) cpnew evdata2(4)
evdata2(5) Der_Energy_error evdata2(7)];
                    der_f1=DER_Forecast_ts(:,xx);
                    [rank_der] = ranking_der (ts, EV_Forecast_ts,
der_f1, day, period);
                    [DER_Forecast_ts, der_schedule, Eremain1,
g]=ecofunction(DER_Forecast_ts, rank_der, der_schedule, evdata_new,
id_rates, timeslot_duration, z, 2);
                    c2=1;
                    for c2=1:size(stolos,1)
                        if stolos(c2,stili+1)==evdata_new(2)
                            break;
                        end;
                    end;
                    if Eremain1>0.01
                        fmv_old=fMV;
                        sched_old=schedule;
                        evdata_new(6)=Eremain1;
                        evdata_new(1)=k-1;
                        evdata_new(3)=evdata_new(3)+1;
                        fd_ts=125-fd(:,xx);
                        [rank_sm] = smart_rank (ts, EV_Forecast_ts,
fd_ts, day, period);
                        [schedule, fMV, tr, fd, Eremain,
g]=smartfunction(rank_sm, schedule, evdata_new, id_rates, fMV, tr, fd,
timeslot_duration, z, 2, der_schedule);
```

```
                        stolos(c2,stili+7)=Eremain;
                        for ttt=k:(evdata_new(1)+evdata_new(3))
                            NoEV_DMD_ts(ttt,1)=4000-fmv_new(ttt,1);
                        end;
                    else
                        stolos(c2,stili+7)=Eremain1;
                    end;
                end;
            end;
        end;
        for feeder=1:32
            if der_real(k,feeder)>DER_Forecast_ts(k,feeder)+0.01
                for grammi=((feeder-1)*100+1):(feeder*100)
                    idd=der_schedule(grammi,1);
                    found2=0;
                    if day>1
                        found=0;
                        for p=1:size(stolos2,1)
                            if
(stolos2(p,stili+1)==idd)&&(stolos2(p,stili)<k)&&(stolos2(p,stili)+stolos2
(p,stili+2)>=k)
                                evdata3=[stolos2(p,stili)
stolos2(p,stili+1) stolos2(p,stili+2) stolos2(p,stili+3)
stolos2(p,stili+4) stolos2(p,stili+5) stolos2(p,stili+6)
stolos2(p,stili+7)];
                                if evdata3(1)<k
                                    found=1;
                                    found2=1;
                                    break;
                                end;
                            end;
                        end;
                        if found==0
                            for p=1:size(stolos2,1)
                                if (stolos2(p,stili+1-
8)==idd)&&(stolos2(p,stili-8)<k)&&(stolos2(p,stili)+stolos2(p,stili+2-
8)>=k)
                                    evdata3=[stolos2(p,stili-8)
stolos2(p,stili+1-8) stolos2(p,stili+2-8) stolos2(p,stili+3-8)
stolos2(p,stili+4-8) stolos2(p,stili+5-8) stolos2(p,stili+6-8)
stolos2(p,stili+7-8)];
                                    found2=1;
                                    break;
                                end;
                            end;
                        end;
                    else
                        for p=1:size(stolos2,1)
                            if
(stolos2(p,stili+1)==idd)&&(stolos2(p,stili)<k)&&(stolos2(p,stili)+stolos2
(p,stili+2)>=k)
                                evdata3=[stolos2(p,stili)
stolos2(p,stili+1) stolos2(p,stili+2) stolos2(p,stili+3)
stolos2(p,stili+4) stolos2(p,stili+5) stolos2(p,stili+6)
stolos2(p,stili+7)];
                                found2=1;
                                break;
```

```
                                end;
                            end;
                        end;
                        if found2==1
                            telos=0;
                            for ww=k:(evdata3(1)+evdata3(3))
                                if
der_schedule(grammi,1+k)<id_rates(grammi,2)
                                    help4=id_rates(grammi,2)-
der_schedule(grammi,1+k);
                                    help5=[der_real(k,feeder), help4,
schedule(grammi,1+ww)];
                                    extra=min(help5);
                                    if extra>0
der_schedule(grammi,1+k)=der_schedule(grammi,1+k)+extra;
der_real(k,feeder)=der_real(k,feeder)-extra;
schedule(grammi,1+ww)=schedule(grammi,1+ww)-extra;
                                        if ww==k

fMV_real(ww,1)=fMV_real(ww,1)+extra;
tr_real(ww,floor((idd)/1000))=tr_real(ww,floor((idd)/1000))+extra;
fd_real(ww,feeder)=fd_real(ww,feeder)+extra;
                                        else
                                            fMV(ww,1)=fMV(ww,1)+extra;
tr(ww,floor((idd)/1000))=tr(ww,floor((idd)/1000))+extra;
fd(ww,feeder)=fd(ww,feeder)+extra;
                                        end;
                                    end;
                                    extra=0;
                                    if der_real(k,feeder)==0
                                        telos=1;
                                        break;
                                    end;
                                end;
                            end;
                            if telos==0
                               for ww=(evdata3(1)+evdata3(3)):-1:(k+1)
                                    if
der_schedule(grammi,1+k)+0.01<id_rates(grammi,2)
                                        help4=id_rates(grammi,2)-
der_schedule(grammi,1+k);
                                        help5=[der_real(k,feeder), help4,
der_schedule(grammi,1+ww)];
                                        extra=min(help5);
                                        if extra>0
der_schedule(grammi,1+k)=der_schedule(grammi,1+k)+extra;
der_schedule(grammi,1+ww)=der_schedule(grammi,1+ww)-extra;
der_real(k,feeder)=der_real(k,feeder)-extra;
DER_Forecast_ts(ww,feeder)=DER_Forecast_ts(ww,feeder)+extra;
                                       end;
                                    end;
                                end;
                            end;
                            found2=0;
                        end;
                    end;
                end;
```

```
            end;
        end;
        for  gr=1:3200
            if schedule(gr,kk)>0
                idd=schedule(gr,1);
                if day>1
                    found=0;
                    for p=1:size(stolos2,1)
                        if stolos2(p,stili+1)==idd
                            evdata2=[stolos2(p,stili) stolos2(p,stili+1)
stolos2(p,stili+2) stolos2(p,stili+3) stolos2(p,stili+4)
stolos2(p,stili+5) stolos2(p,stili+6) stolos2(p,stili+7)];
                            if evdata2(1)<k
                                found=1;
                                break;
                            end;
                        end;
                    end;
                    if found==0
                        for p=1:size(stolos2,1)
                            if stolos2(p,stili+1-8)==idd
                                evdata2=[stolos2(p,stili-8)
stolos2(p,stili+1-8) stolos2(p,stili+2-8) stolos2(p,stili+3-8)
stolos2(p,stili+4-8) stolos2(p,stili+5-8) stolos2(p,stili+6-8)
stolos2(p,stili+7-8)];
                                break;
                            end;
                        end;
                    end;
                else
                    for p=1:size(stolos2,1)
                        if stolos2(p,stili+1)==idd
                            evdata2=[stolos2(p,stili) stolos2(p,stili+1)
stolos2(p,stili+2) stolos2(p,stili+3) stolos2(p,stili+4)
stolos2(p,stili+5) stolos2(p,stili+6) stolos2(p,stili+7)];
                            break;
                        end;
                    end;
                end;
                isxis=schedule(gr,kk);
                [Perror, fMV_real, tr_real,
fd_real]=dispatch_function(idd, k, isxis, fMV_real, tr_real, fd_real);
                schedule(gr,kk)=schedule(gr,kk)-Perror;
                total_DMD(k,1)= total_DMD(k,1)+ (isxis-Perror);
            end;
        end;
        while stolos(c,stili)==k
            evdata=[stolos(c,stili) stolos(c,stili+1) stolos(c,stili+2)
stolos(c,stili+3) stolos(c,stili+4) stolos(c,stili+5) stolos(c,stili+6)];
           t=floor(evdata(2)/1000);
            f=floor(mod(evdata(2),1000)/100);
            wwww=(t-1)*4+f;
            Eremain1=evdata(6);
            if types(2,1)==1
                der_f1=DER_Forecast_ts(:,wwww);
                [rank_der] = ranking_der (ts, EV_Forecast_ts, der_f1, day,
period);
```

```
                [DER_Forecast_ts, der_schedule, Eremain1,
g]=ecofunction(DER_Forecast_ts, rank_der, der_schedule, evdata, id_rates,
timeslot_duration, z, 1);
            end;
            if Eremain1>0
                evdata(6)=Eremain1;
                if types(1,1)==1
                    [schedule, fMV, tr, fd, Eremain,
g]=dumpfunction(schedule, evdata, id_rates, fMV, tr, fd,
timeslot_duration, 1);
                else
                    fd_ts=125-fd(:,wwww);
                    [rank_sm] = smart_rank (ts, EV_Forecast_ts, fd_ts,
day, period);
                    [schedule, fMV, tr, fd, Eremain,
g]=smartfunction(rank_sm, schedule, evdata, id_rates, fMV, tr, fd,
timeslot_duration, z, 1, der_schedule);
                end;
                stolos(c,stili+7)=Eremain;
            else
                stolos(c,stili+7)=Eremain1;
            end;
            for w=1:evdata(3)
                NoEV_DMD_ts(evdata(1)+w,1) =
NoEV_DMD_ts(evdata(1)+w,1)+schedule(g,1+evdata(1)+w);
            end;
            if c<size(stolos,1)
                c=c+1;
            else
                break;
            end;
        end;
    end;
end;
%*************************** End ***************************
% jtcp('close',JTCPOBJ);
```

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