THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

# Energy Scheduling of Electric Vehicles for Electricity Market Participation

PAVAN BALRAM

*Division of Electric Power Engineering*

Department of Energy and Environment

CHALMERS UNIVERSITY OF TECHNOLOGY

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PAVAN BALRAM



Thesis for the degree of Licentiate of Engineering
Department of Energy and Environment
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone: +46 (0)31-772 1000

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PAVAN BALRAM
Department of Energy and Environment
Chalmers University of Technology


# Abstract

Global policy targets to reduce greenhouse gas emissions has led to increased interest in electric vehicles (EV) and their integration into the electricity network. Batteries in EVs offer flexibility from the demand side that could potentially compete against generating resources for providing power system services. Existing power markets, however, are not well suited to encourage direct participation of flexible demand from small consumers such as EV owners. The introduction of an aggregator agent with the functions of gathering and representing the energy needs of EV owners in electricity markets could prove useful in this regard.

In this thesis, mathematical models are developed for optimizing the EV aggregator agent's: a) energy schedule for day-ahead electricity market participation, b) energy schedule for regulating power market (RPM) participation and c) energy portfolio to determine the power contracts to be obtained from forward electricity market. The modeling is done by accumulating individual vehicle batteries and treating them as a single large battery. The centralized charging and discharging of this battery is then scheduled based on the traveling needs of the EV owners determined by an aggregated driving profile and the cumulative electrical energy needs of vehicles over the optimization horizon. Two methods for scheduling EV demand, named as joint scheduling method (JSM) and aggregator scheduling method (ASM), are presented. The developed methods are then applied on selected test systems to observe the effects of EV demand scheduling on prices in the day-ahead, regulating power and retail markets.

The results from the day-ahead market case study indicate that the scheduling of EV energy using JSM at high EV penetration levels of 75-100% could lead to lowering of day-ahead market prices as compared to a simpler control method such as fixed period charging. Results from RPM case study indicate that EV aggregator could potentially perform arbitrage provided that they plan and bid competitively against other market players, while considering the additional costs associated with vehicle-to-grid discharge. The case study results from energy portfolio optimization of the aggregator point to the monetary benefits from demand flexibility of EV batteries to both the electricity retailer, in the form of increased profits, and to EV owners through higher cost savings. It was found that the savings by customers could be attained provided that the ratio of variable to fixed price retail contracts is greater than 30:70 for a 10% EV penetration level and exceeds 50:50 for a 30% EV penetration level.


Keywords: Electric vehicles, demand response, EV aggregator, day-ahead market, regulating power market, retailer planning

*to my parents...*

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Pavan Balram

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# List of Abbreviations

| | |
|---|---|
| EU | European Union |
| EV | Electric vehicle |
| GHG | Greenhouse gases |
| DG | Distributed generators |
| ESS | Energy storage systems |
| CL | Controllable loads |
| DSM | Demand side management |
| DR | Demand response |
| DAM | Day-ahead market |
| DSO | Distribution system operator |
| TSO | Transmission system operator |
| DS | Deferred settlement |
| EPAD | Electricity price area differentials |
| CfD | Contracts for difference |
| PJM | Pennsylvania-Jersey-Maryland |
| CSP | Curtailment service provider |
| ICT | Information and communication technology |
| ICE | Internal combustion engine |
| HEV | Hybrid electric vehicle |
| PHEV | Plug-in hybrid electric vehicle |
| BEV | Battery electric vehicle |
| PEV | Plug-in electric vehicle |

| | |
|---|---|
| SOC | State of charge |
| JSM | Joint scheduling method |
| ASM | Aggregator scheduling method |
| NO | Bidding area in Norway |
| SE | Bidding area in Sweden |
| FI | Bidding area in Finland |
| DK | Bidding area in Denmark |
| NTC | Net transfer capacity |
| RPM | Regulating power market |
| BRP | Balance responsible party |
| OPF | Optimal power flow |
| ACOPF | Alternating current optimal power flow |
| DCOPF | Direct current optimal power flow |
| ITL | Incremental transmission loss |
| LMP | Locational marginal price |
| RP | Retailer Planning |
| GAMS | General Algebraic Modeling System |
| VPP | Virtual power plant |

# List of Symbols

### Sets

| | |
|---|---|
| $T$ | Set of time periods in the planning horizon |
| $MG$ | Set of generating units |
| $N$ | Set of buses in the system |
| $N_G$ | Set of generator buses in the system |
| $N_L$ | Set of transmission lines in the system |
| $N_V$ | Set of EV buses in the system |
| $H$ | Set of hourly time periods in EV aggregator model |
| $W$ | Set of scenarios |
| $Y$ | Set of planning years |
| $Q$ | Set of planning quarters |
| $M$ | Set of planning months |

### Parameters

| | |
|---|---|
| $VC_m$ | Variable cost of generation of generating unit $m$ [€/MWh] |
| $SC_m$ | Start-up cost of generating unit $m$ [€] |
| $P_m^{max}$ | Maximum active power output of generator unit $m$ [MW] |
| $P_m^{min}$ | Minimum active power output of generator unit $m$ [MW] |
| $SU_m$ | Start up ramp limit of generating unit $m$ [MW/h] |
| $SD_m$ | Shut down ramp limit of generating unit $m$ [MW/h] |
| $RU_m$ | Ramp-up limit of generating unit $m$ [MW/h] |

| | |
|---|---|
| $RD_m$ | Ramp-down limit of generating unit $m$ [MW/h] |
| $UT_m$ | Minimum up time of generating unit $m$ [h] |
| $DT_m$ | Minimum down time of generating unit $m$ [h] |
| $GU_m$ | Number of periods that generating unit $m$ must be online at the beginning of the DAM optimization horizon due to its minimum up time constraint [h] |
| $GD_m$ | Number of periods that generating unit $m$ must be offline at the beginning of the DAM optimization horizon due to its minimum down time constraint [h] |
| $S_m^0$ | Time periods that generating unit $m$ has been offline at the beginning of the DAM optimization horizon [h] |
| $U_m^0$ | Time periods that generating unit $m$ has been online at the beginning of the DAM optimization horizon [h] |
| $V_m^0$ | Initial commitment status of generating unit $m$. 1 if is online and 0 if it is offline |
| $SOC^{max}$ | Aggregated maximum energy level of battery vehicles [MWh] |
| $SOC^{min}$ | Aggregated minimum energy level of battery vehicles [MWh] |
| $SOC^{ini}$ | Aggregated initial energy level of battery vehicles [MWh] |
| $E_t^{next}$ | Aggregated energy required by battery vehicles for next day travel at time $t$ [MWh/h] |
| $C_t^L$ | Aggregator forecasted conventional load at time $t$ [MWh/h] |
| $a_1, a_0$ | Co-efficients in estimated supply function |
| $SOC_i^{max}$ | Aggregated maximum energy level of battery vehicles at bus $i$ [MWh] |
| $SOC_i^{min}$ | Aggregated minimum energy level of battery vehicles at bus $i$ [MWh] |
| $SOC_i^{ini}$ | Aggregated initial energy level of battery vehicles at bus $i$ [MWh] |
| $E_{i,t}^{next}$ | Aggregated energy required by battery vehicles for next day travel at bus $i$ at time $t$ [MWh/h] |
| $E_{i,t}^{up}$ | Planned up-regulating energy to be discharged at bus $i$ at time $t$ [MWh/h] |
| $P_i^{max}$ | Maximum active power output of generator at bus $i$ [MW] |
| $P_i^{min}$ | Minimum active power output of generator at bus $i$ [MW] |
| $Q_i^{max}$ | Maximum reactive power output of generator at bus $i$ [MVAr] |

| | |
|---|---|
| $Q_i^{min}$ | Minimum reactive power output of generator at bus $i$ [MVAr] |
| $V_i^{max}$ | Maximum voltage magnitude limit at bus $i$ [kV] |
| $V_i^{min}$ | Minimum voltage magnitude limit at bus $i$ [kV] |
| $L_{i,j}^{max}$ | Maximum active power capacity of transmission line between buses $i$ and $j$ [MW] |
| $P^{R+}$ | Reserve requirement for up regulation [MW] |
| $P^{R-}$ | Reserve requirement for down regulation [MW] |
| $P_i^{dev}$ | Real time deviation in active power at bus $i$ [MW] |
| $B_{i,j}$ | Susceptance element ($i$,$j$) of ac network admittance matrix [p.u] |
| $PL_{i,t}$ | Active power demand at bus $i$ at time $t$, respectively [MW] |
| $QL_{i,t}$ | Reactive power demand at bus $i$ at time $t$, respectively [MVAr] |
| $DP_{i,t}$ | Aggregated battery discharging power of vehicles at bus $i$ at $t$ [MW] |
| $CP_{i,t}$ | Aggregated battery charging power of vehicles at bus $i$ at time $t$ [MW] |
| $ptdf_{i,j,k}$ | Change in flow over line between buses $i$ and $j$ from power injection at bus $k$ |
| $E_t^C(w)$ | Conventional demand at time $t$ in scenario $w$ [MWh/h] |
| $E_h^{next}$ | Aggregated energy required by battery vehicles for next day travel at time $h$ [MWh/h] |
| $\pi_t^S(w)$ | Estimated spot price at time $t$ in scenario $w$ [€/MWh] |
| $\pi_h^S$ | Estimated spot price at time $h$ [€/MWh] |
| $\pi_t^{Ybase}$ | Base yearly forward price at time $t$ [€/MWh] |
| $\pi_t^{Qbase}$ | Base quarterly forward price at time $t$ [€/MWh] |
| $\pi_t^{Mbase}$ | Base monthly forward price at time $t$ [€/MWh] |
| $\rho^Y$ | Slope of yearly forward price function [€/MW$^2$h] |
| $\rho^Q$ | Slope of quarterly forward price function [€/MW$^2$h] |
| $\rho^M$ | Slope of monthly forward price function [€/MW$^2$h] |
| $prob(w)$ | Probability of scenario $w$ |
| $vy_{yt}$ | Binary parameter to indicate maturity of yearly forward contract at time $t$ in year $y$ |

| | |
|---|---|
| $vq_{qt}$ | Binary parameter to indicate maturity of quarterly forward contract at time $t$ in quarter $q$ |
| $vm_{mt}$ | Binary parameter to indicate maturity of monthly forward contract at time $t$ in month $q$ |
| $P_t^D(w)$ | Total end user demand at time $t$ in scenario $w$ [MWh/h] |
| $E_t(w)$ | Charging energy of EVs scheduled at time $t$ in scenario $w$ of RP model [MWh/h] |
| $P^{maxF}$ | Maximum power traded with fixed retail contract [MWh/h] |
| $P^{maxV}$ | Maximum power traded with variable retail contract [MWh/h] |
| $\nu^F$ | Fraction of customer demand with fixed price contracts |
| $\nu^V$ | Fraction of customer demand with variable price contracts |
| $\theta^F$ | Slope of fixed retail contract price determination curve [€/MW$^2$h] |
| $\theta^V$ | Slope of variable retail contract price determination curve [€/MW$^2$h] |
| $R_t^V(w)$ | Revenue from variable contract at time $t$ in scenario $w$ [€/h] |
| $\lambda_t^V(w)$ | Selling price for variable contract at time $t$ in scenario $w$ [€/MWh] |
| $\alpha$ | Confidence level for calculation of $CVaR$ |
| $\beta$ | Risk weight factor [0,1] |

**Variables**

| | |
|---|---|
| $E_t$ | Aggregated charging energy to be scheduled at time $t$ [MWh/h] |
| $SOC_t$ | Aggregated energy level of battery vehicles at time $t$ [MWh] |
| $\hat{\pi}_t^s$ | Day-ahead price forecasted using supply function at time $t$ [$/MWh] |
| $DAMC$ | Total cost from day-ahead market model [€] |
| $ACC$ | Total charging cost estimated by aggregator [€] |
| $p_{m,t}$ | Active power output of generator unit $m$ at time $t$ [MW] |
| $v_{m,t}$ | Binary variable indicating online status of generator unit $m$ at time $t$. Unit is online if value is 1 and offline if value is 0 |
| $y_{m,t}$ | Binary variable indicating start-up status of generator unit $m$ at time $t$. Unit has started up if value is 1 and offline if value is 0 |

| | |
|---|---|
| $z_{m,t}$ | Binary variable indicating shut down status of generator unit $m$ at time $t$. Unit is shut down if value is 1 and online if value is 0 |
| $SOC_{i,t}$ | Aggregated energy level of battery vehicles at bus $i$ at time $t$ [MWh/h] |
| $DAEC$ | Total day-ahead cost estimated by aggregator using DCOPF [€] |
| $DAC_t$ | Total day-ahead cost from ACOPF at time $t$ [€] |
| $C_i(P_{i,t})$ | Production cost function of generator at bus $i$ [€] |
| $P_{i,t}$ | Active power output of generator at bus $i$ at time $t$ [MW] |
| $E_{i,t}$ | Aggregated charging energy to be scheduled by EV aggregator model at bus $i$ at time $t$ [MWh/h] |
| $L_{i,j}$ | Active power flow over line between buses $i$ and $j$ from spot market scheduling [MW] |
| $V_i$ | Voltage magnitude at bus $i$ [kV] |
| $\delta_{i,t}$ | Voltage angle at bus $i$ at time $t$ [rad] |
| $\Delta EV_i^+$ | Total up regulating power from EVs at bus $i$ [MW] |
| $\Delta EV_i^-$ | Total down regulating power from EVs at bus $i$ [MW] |
| $\Delta P_i^+$ | Up regulating power volume by BRP at bus $i$ [MW] |
| $\Delta P_i^-$ | Down regulating power volume by BRP at bus $i$ [MW] |
| $RP$ | Total cost of obtaining regulating power [€] |
| $c_i^+$ | Up regulating price by BRP at bus $i$ [€/MWh] |
| $c_i^-$ | Down regulating price by BRP at bus $i$ [€/MWh] |
| $ac_i$ | Adjusted up or down regulating price at bus $i$ [€/MWh] |
| $ITL_i$ | Incremental transmission loss at bus $i$ |
| $PF_i$ | Penalty factor at bus $i$ |
| $RPO$ | Objective function of retailer planning model [€] |
| $E_h$ | Charging energy of EVs to be scheduled at time $h$ in EV aggregator model [MWh/h] |
| $SOC_h$ | Energy level in EV batteries at time $h$ [MWh/h] |
| $C_t^F$ | Cost from forward contracts at time $t$ [€/h] |
| $C_t^S(w)$ | Cost from spot market purchase at time $t$ in scenario $w$ [€] |
| $\pi_t^{FY}$ | Unit price of yearly forward contracts [€/MWh] |
| $\pi_t^{FQ}$ | Unit price of quarterly forward contracts [€/MWh] |

| | |
|---|---|
| $\pi_t^{FM}$ | Unit price of monthly forward contracts [€/MWh] |
| $P_t^{FY}$ | Power purchased through yearly forward contracts at time $t$ [MWh/h] |
| $P_t^{FQ}$ | Power purchased through quarterly forward contracts at time $t$ [MWh/h] |
| $P_t^{FM}$ | Power purchased through monthly forward contracts at time $t$ [MWh/h] |
| $P_y^{Y}$ | Power purchased through yearly forward contracts over the year $y$ [MWh] |
| $P_q^{Q}$ | Power purchased through quarterly forward contracts over the quarter $q$ [MWh] |
| $P_m^{M}$ | Power purchased through monthly forward contracts over the month $m$ [MWh] |
| $P_t^{S}(w)$ | Power purchased from spot market at time $t$ in scenario $w$ [MWh/h] |
| $R_t^{F}(w)$ | Revenue from fixed contract at time $t$ in scenario $w$ [€/h] |
| $\lambda_t^{F}(w)$ | Selling price for fixed contract at time $t$ in scenario $w$ [€/MWh] |
| $CVO$ | Objective function of CVaR optimization problem [€] |
| $\xi$ | Auxiliary variable used for calculation of $CVaR$ [€] |
| $\eta(w)$ | Second auxiliary variable used for calculation of $CVaR$ [€] |

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# Chapter 1

# Introduction

*This chapter provides an overview of the motivations behind the presented research work, the main contributions by the author and resulting scientific publications.*

## 1.1 Background and Motivation

The electric distribution systems are faced with continually developing challenges with regards to large-scale integration of distributed generation (DG) from wind and solar resources. The intermittent nature of these resources results in an overall decrease in controllability on the supply side. A solution to this problem could be to increase the level of controllability on the demand side to effectively make the intermittent DG resources dispatchable and extend their functionalities over wider time periods [1]. This could partly alleviate the challenge of immediate need for network reinforcement for accommodating large amount of intermittent DG in the distribution system [2].

Demand-side resources could include controlling certain existing controllable loads (CL) such as refrigeration systems within households or energy storage systems (ESS) including space heating, battery energy storage elements in future plug-in (hybrid) electric vehicles (EV) and large battery energy storage solution owned and controlled by utilities. These potential solutions are facilitated by smart measurement systems by obtaining real-time estimation of energy consumption of demand side elements and through the use of power electronic devices to achieve the necessary level of controllability in active and reactive power exchange with the network. However, rules and regulations need to enable the participation of small and medium scale demand resources in electricity markets. This could result in more efficient use of resources within the market, provide greater benefits for the customers and result in increased integration of intermittent renewable resources.

Methods for electrical energy storage have always been considered as an attractive prospect by engineers. The challenge has been to store electrical energy in an economical way. Large scale roll-out of electric vehicles and smart metering devices coupled with the integration of advanced information and communication infrastructure in the power system could result in a new potential for storing electricity in vehicle batteries. By aggregating and controlling the charging and discharging of these storage elements, it could be possible to provide greater opportunities for demand response [3] while reducing the impacts of increased energy consumption from these new power system elements.

Research work have been previously carried out to study the impact of large scale introduction of electric vehicles on power systems [4]–[7]. In [8], an EV charging control scheme is proposed by obtaining demographic statistical data and estimating the charging behavior to study the impacts on the distribution network. Results from these works have indicated the need for controlled charging of vehicles in order to reduce the stress created by heavy roll out of these new types of demand on the transmission and distribution systems. However, there is a need to develop models and study the impacts of EVs and their scheduled demand on market price of electricity in order to quantify the monetary benefits obtained by customers, if any.

In [9], an optimization framework is proposed, in which, demand response resources are aggregated and their consumption schedules are optimized for their participation in day-ahead energy markets. [10] proposes an optimization algorithm EV flexibility planning and participation in manual reserve markets while [11] has developed an approach to optimize the charging schedules for day-ahead and secondary reserve markets. Papers [12], [13] have proposed optimal biding strategies for EV participation in day-ahead electricity markets.

However, there is a need to develop models for optimizing EV battery charging and discharging energy in order to observe the effect of controlled EV demand on market price in the day-ahead and regulating power markets. In addition, it is also imperative to develop an energy portfolio optimization model for an electricity retailer who represents these flexibilities in various markets. This optimization approach should account for the price and energy demand risks faced by the retailer in physical markets, make decisions regarding hedging in forward electricity markets and subsequently set appropriate retail prices to its customers. This research work tries to address the above mentioned points. The developed scheduling models and decision making framework are presented in detail in the upcoming chapters.

## 1.2 Objectives and Main Contributions

The main aim of this thesis is to develop methods for energy scheduling by an EV aggregator for electricity market participation. To accomplish this, mathematical models to schedule EVs' energy by an aggregator for its participation in day-ahead and regulating power power markets have been developed. Furthermore, a planning approach has been developed for an electricity retailer to assume the market functions of the aggregator and plan for contracting electricity from the forward market. The proposed models have been implemented in a generic optimization software platform and applied to perform case studies.

The main contribution of this thesis could be outlined as follows:

- Methods for EV energy scheduling by the aggregator are developed under two different day-ahead market paradigms. The first, named as the joint scheduling method, considers a joint dispatch of generators and EV battery energy while the second, named as the aggregator scheduling method, considers independent planning by the aggregator.
- A planning model for EV aggregator's participation in regulating power market is developed. In this model, the aggregator scheduling method is extended to also plan for the deviations that could occur after the clearing of the day-ahead market. Additionally, a modified clearing mechanism of the RPM is proposed where the regulating power resources are activated based on a re-valued regulation price that reflects the resource's impact on active power loss within the transmission network.
- An approach is proposed for an electricity retailer to presume the market functions of an aggregator and plan for medium-term hedging against the price volatility and energy demand uncertainty in the forward market. The mathematical model developed for this purpose could also be used to determine the retail prices that the retailer could offer to its end consumers based on two different types of retail contracts.

## 1.3 Thesis Outline

The thesis is organized as follows:

- **Chapter 2** gives a brief overview of select electricity markets around the world and state-of-the-art regarding demand response.
- **Chapter 3** describes an EV aggregator model for its participation in the day-ahead electricity market along with case studies performed on an IEEE 30-bus test system and a Nordic test system to observe the effects of EV charging on system demand profile and market price of electricity.
- **Chapter 4** presents a regulating power market model incorporating energy scheduling by EV aggregator along with a case study on the Nordic 32-bus test system to study the effects of EV aggregator contribution on regulating power prices and the corresponding regulation cost.
- **Chapter 5** details the proposed optimization model of an electricity retailer that incorporates the market functions of an EV aggregator to obtain power contracts from the forward market and determine the retail prices to be offered to its end customers. The model is used in a case study with data from a typical electricity retailer in Sweden to investigate the impacts of scheduled charging of EV on retail

prices of electricity in the presence of two types of retail contracts offered by the retailer.

- **Chapter 6** concludes the thesis and gives some ideas for future research work.

## 1.4 List of Publications

The content of this thesis is based on the following published articles:

I **P. Balram**, L. A. Tuan, and L. Bertling Tjernberg, "Effects of plug-in electric vehicle charge scheduling on the day-ahead electricity market price," 3rd IEEE PES International Conference on Innovative Smart Grid Technologies (ISGT Europe), Berlin, Oct., 2012.

II **P. Balram**, L. A. Tuan, and L. Bertling Tjernberg, "Stochastic programming based model of an electricity retailer considering uncertainty associated with electric vehicle charging," 10th International Conference on the European Energy Market (EEM), Stockholm, May, 2013.

III **P. Balram**, L. A. Tuan, and L. Bertling Tjernberg, "Modeling of Regulating Power Market Based on AC Optimal Power Flow Considering Losses and Electric Vehicles," IEEE PES International Conference on Innovative Smart Grid Technologies (ISGT Asia), Bangalore, Nov., 2013.

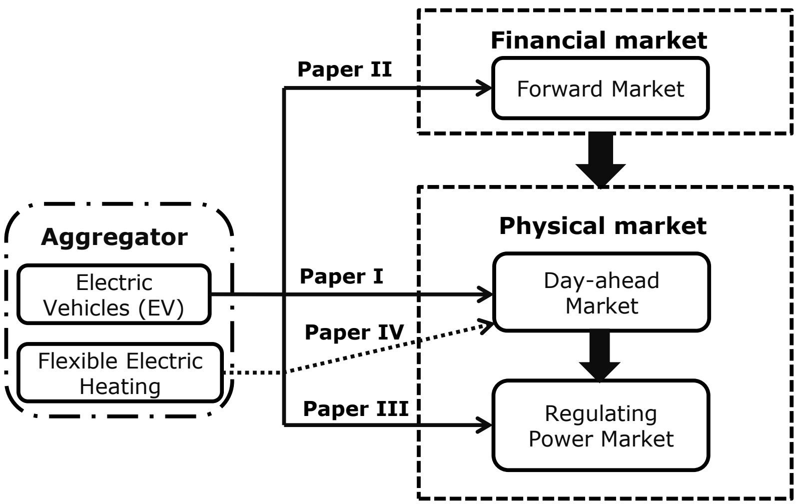


Figure 1.1: Overview of published articles in this thesis

The author has also contributed to the following article not included in this thesis:

IV D. Steen, **P. Balram**, L. A. Tuan, L. Reichenberg, L. Bertling Tjernberg, "Impact Assessment of the Coordination between Wind Power and Demand Side Management on Spot Market Prices," Submitted to Innovative Smart Grid Technologies (ISGT Europe), Istanbul, Oct., 2014.

An overview of the published articles presenting the EVs' participation in respective electricity markets are shown in Figure 1.1

# Chapter 2

# Electricity Markets and Demand Response

*This chapter gives an overview of demand response and the role of future electric vehicles. A basic understanding of the Nordic electricity market is also provided and the function of a new agent responsible for trading demand side flexibilities in electricity markets is described.*

## 2.1 Demand Side Management

Historically, power system planning has been focused on building strong bulk generation and transmission systems with little focus on demand side. The traditional philosophy of power system operation has been to control the generator systems and transmission components to ensure load following. Only in extreme situations would there be exceptions leading to load shedding or interruption. With the increased integration of intermittent energy resources and rising volatility in fossil fuel prices, utilities have begun to shift their operating philosophy towards better utilization of demand side resources. Hence, greater incentives for consumers to participate in demand control programs have begun to be rolled out with industrial consumers, among others, being the largest contributors. Adoption of such programs provides a stepping stone for electricity markets to seamlessly imbibe demand resources to compete with power producers to provide power system services.

Demand side management (DSM) refers to a set of policies and measures that influence customer use of electricity, ranging from long-term load conservation and growth targets to short-term direct and indirect control of energy resources. Various organization have attempted to provide a description for the term. Notable among them could be the following:

- According to the Institute of Electrical and Electronics Engineers (IEEE) terminology task force [14], it *"encompasses the entire range of management functions associated with directing demand-side activities, including program planning, evaluation, implementation, and monitoring."*

- International Electrotechnical Commission (IEC) [15] defines DSM as a *"process that is intended to influence the quantity or patterns of use of electric energy consumed by end-use customers ."*

During the 1970-80s, vertically integrated utilities classified DSM based on several load shaping strategies [16], which could be highly relevant even under the deregulated market paradigm. As shown in Figure 2.1, DSM could be broadly categorized to include- strategic load conservation, strategic load growth and demand response [17], [18]. Out of the three, strategic load conservation and strategic load growth could be considered as long-term objectives whereas demand response could be a short-term objective. Each of the terms are further explained below.

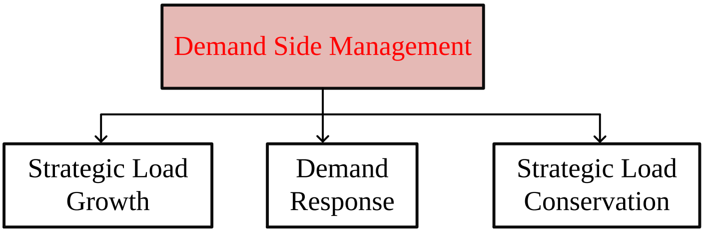


Figure 2.1: Categorization of DSM based on load shaping strategies

### 2.1.1 Strategic Load Conservation

Strategic conservation is the change in load shape that results from programs directed at overall reduction in end-user demand for electricity that could include alterations in the consumption pattern of end users. This is shown in Figure 2.2.

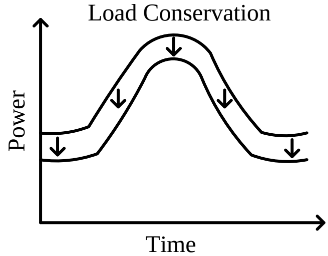


Figure 2.2: Change in load profile due to strategic load conservation

Two common programs aimed in this direction are:

- Energy efficiency- efficient processes use less input energy to provide the same quantity of energy output. E.g., using fluorescent lamps produce the same luminescence using less electricity as compared to incandescent lamps. Currently, one of the EU energy policy targets for 2020 includes increasing the overall energy efficiency by 20%.
- Energy conservation- is the intentional reduction in energy use through changes in consumption patterns etc. E.g., switching off lamps when not in use is a good energy conservation practice.

### 2.1.2 Strategic Load Growth

Strategic load growth is the change in load shape that results from an overall increase in end-user demand for electricity. A typical change in load shape due to strategic load growth is shown in Figure 2.3. This could be a result of economic growth within a region or due to an increase in a new class of demand. E.g., increased share of electric heating at homes as opposed to district heating and electrification of new regions within developing countries.

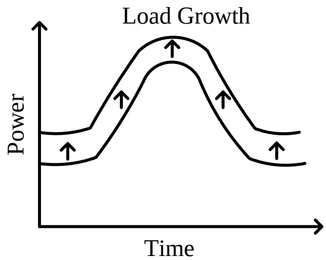


Figure 2.3: Change in load profile due to strategic load growth

### 2.1.3 Demand Response

Demand response is the independent variation in consumption made by consumers as a reaction to some form of incentive. This incentive could be price signals from an effective market for electricity or it could be a signal provided by the distribution system operator (DSO) in order to maintain the security and reliability of the power system during emergency conditions. Regardless of the type of incentive used, the end result of demand response is one of the following load shaping objectives:

- Peak Clipping: is the reduction of peak load by using direct load control over customers' appliances. This form of control could be used to reduce the overall cost and dependence on peaking generating units. A good example of peak clipping is the use of interruptible or curtailable tariffs for industrial customers in many vertically integrated power system architectures. The change in load profile due to peak clipping is shown in Figure 2.4.

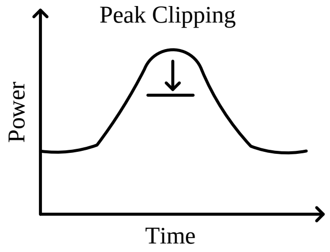


Figure 2.4: Change in load profile due to peak clipping

- Valley Filling: is the process where incentives are provided to increase new demand during off-peak hours. This could be accomplished, e.g., by providing price incentives to new space heating or electric vehicle demand to consume during off-peak hours. Changes in load profile due to valley filling occur as shown in Figure 2.5.

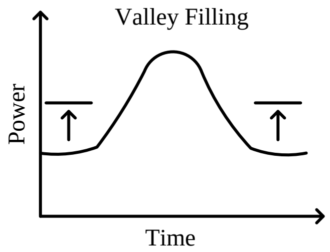


Figure 2.5: Change in load profile due to valley filling

- Load Shifting: is shifting part of the load from on-peak to off-peak periods. This could involve displacing loads during a particular hour that would otherwise normally be served by electricity. This is shown in Figure 2.6.

- Flexible Load Shaping: is the detailed planning of load shape by offering a combination of various incentives. These incentives could include interruptible load, integrated energy management systems or individual customers' load control, etc. Effect of flexible load shaping on load profile is shown in Figure 2.7.

The consumers who are willing to respond to incentive-based signals are referred to as active consumers. An active consumer could be either a large industrial consumer or a small domestic consumer. Since, the consumption levels of domestic consumers are small compared to the volumes traded in electricity markets, an agent similar to a retailer could

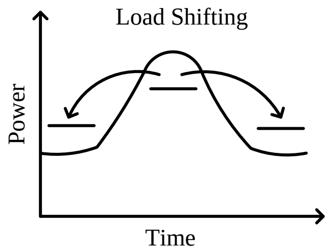


Figure 2.6: Change in load profile due to load shifting

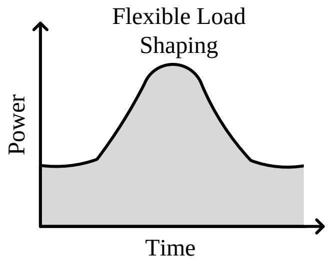


Figure 2.7: Change in load profile due to load shaping

become essential to represent the needs of domestic consumers in electricity markets. With controllable resources, however, this agent generally referred to as an 'aggregator' could possibly assume new functions that might require it to control consumer appliances in real-time.

In this thesis, the aggregator is assumed to use the flexible load shaping strategy based on price signals from the electricity market and subsequently offer appropriate retail prices to its customers based on the type of retail contract. The aggregator is assumed to provide greater benefits by offering larger discounts on the retail prices to its customers who change their consumption pattern.

## 2.2 Overview of Nordic Electricity Markets

The electricity market is an arrangement for purchase and sale of electrical energy as a commodity between various free players- producers, consumers, retailers and traders. Additional players such as transmission system operators (TSO) and DSO facilitate the functioning of electricity markets and the subsequent delivery of electrical energy to end consumers. The power generated by the producers is delivered to consumers through transmission and distribution networks. As the electricity network acts as a common platform for the delivery of energy, the network owners are generally established monopolies that are independent and neutral. The producers and consumers pay a fee known as the *'point tariff'* to the network owners for every kWh of electric energy produced into or consumed from the grid. This ensures that the market mechanism is facilitated, while ensuring financial compensation to the TSO/DSO for managing network related operations [19].

An overview of market participants along with the various types of contracts they could enter into is shown in Figure 2.8.

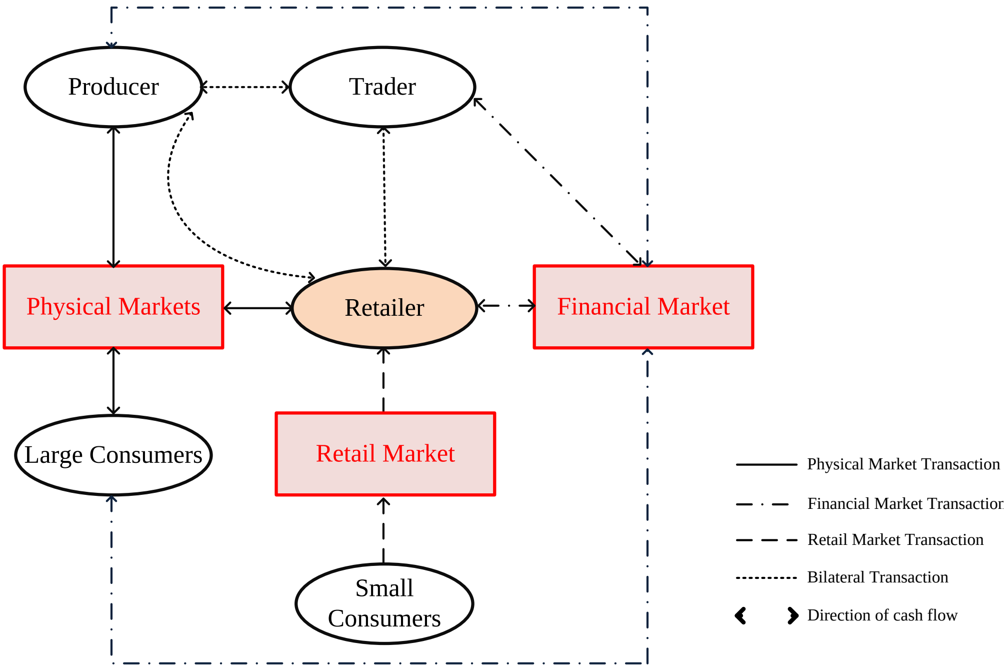


Figure 2.8: Market players and their interactions within an electricity market framework

A figurative description of the participation of a typical retailer in various markets is shown in Figure 2.9.

Many of the electricity markets within the European Union (EU) and other parts of the world have a structure similar to that of the Nordic electricity market and are constantly evolving. However, considering the EU level plan of a harmonized electricity market to facilitate cross-border trading [20], it could be reasonably assumed that future developments would not drastically change the framework of electricity markets from the present. Currently, market players can enter into various power contracts that are further described below in the context of the Nordic electricity market.

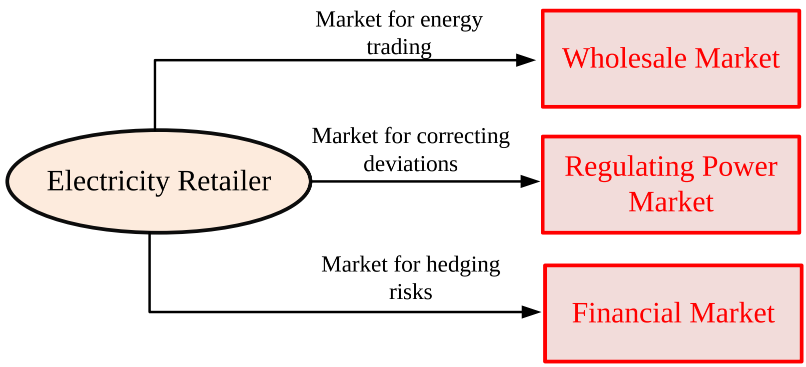


Figure 2.9: Overview of retailer participation in physical and financial markets

### 2.2.1 Bilateral Contracts

Market participants can enter into more conventional *bilateral contracts* that involve a direct trade between a buyer and seller of electrical energy. Considering around 84% of power consumption in the Nordic and Baltic countries are bought at the day-ahead market (DAM) [21], it can be seen that electricity market trading is becoming more appealing to the players.

### 2.2.2 Physical Electricity Markets

Like many other commodities, electricity could also be traded within a wholesale market framework. A common DAM called *Elspot* exists for the Nordic and Baltic countries where the market players trade bulk of the energy production and consumption. The clearing of *Elspot* results in a production and/or consumption plan for each market player with a delivery obligation, which requires the players to abide by their individual plans.

Electrical energy is however, dynamic, in the sense that energy has to be instantaneously available when there is demand with few economically viable storage options. This singular characteristic along with the fact that *Elspot* is cleared ahead of the delivery time of electricity necessitates the use of forecasting methods by the players to estimate their production and consumption. The resulting power deviations that could occur due to forecasting errors, component failures etc., need to be rectified. Players are provided an opportunity to do this through the continuously traded *Elbas* market that is available to balance out the players' individual deviations from their *Elspot* plans.

It is still possible that last minute imbalances could occur due to failure of components or various faults within the power system. The responsibility of maintaining power balance within the power system during delivery period rests on the TSO who jointly operate the *regulating power market* to provide a mechanism for correcting the resulting imbalance during delivery period and ensure the desired level of security of supply within the power system. This market is cleared retroactively as opposed to the *Elbas* market.

There is a physical obligation associated with the electricity markets, i.e., it has to be ensured that the energy traded in the market is delivered to the end consumers during the specified delivery period. Hence, the Elspot, Elbas and regulating power markets are collectively addressed as *physical markets*.

### 2.2.3 Financial Electricity Market

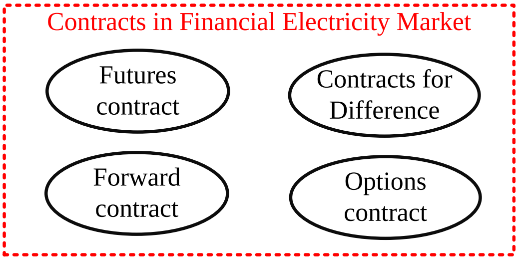


Figure 2.10: Overview of contracts in financial electricity markets

It is imperative that the market players are able to quantify and hedge the financial risks associated with their participation in the physical markets. *Financial market* provides a platform to manage risks by hedging against price fluctuations in the wholesale markets. Numerous contracts are available in a financial market [22] as shown in Figure 2.10.

Specifically, four contract types are offered to market players participating in the Nordic power markets-

- Power Futures
- Power Deferred Settlement (DS) Futures, formerly known as 'Power Forward'
- Electricity Price Area Differentials (EPAD), formerly known as Contracts for difference (CfD)
- Power Options

It is also important to mention that the financial and physical markets have a specific time-line over which they are operated. Financial markets are cleared days, weeks, months or years ahead of delivery as opposed to physical markets that are generally cleared 45 minutes to one day-ahead. An overview of the time-line for Nordic physical and financial markets operation is shown in Figure 2.11.

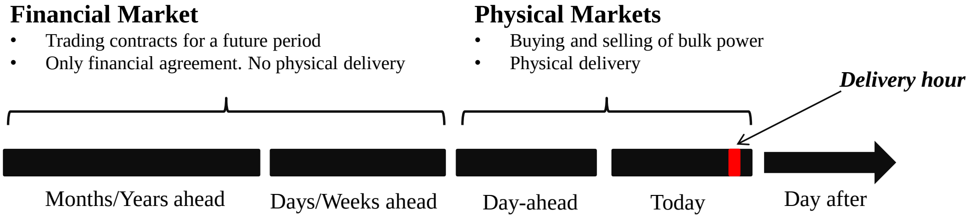


Figure 2.11: Overview of timeline of Nordic physical and financial markets

## 2.3 Demand Response in Electricity Markets

Conventionally, end consumers have been exposed to fixed average electricity rates and hence, shielded from short-term variations in prices due to varying cost of electricity generation. As a result, consumers have had a tendency to over-consume during demanding hours without any control from network owners- e.g., during winter season, when surrounding temperature drops, the electric heating load could drastically increase within all domestic households leading to a significantly greater demand for electricity- in a hydro power dominated region, the water availability in the reservoirs is moderate that could increase generation from other fossil fuels that have significantly higher marginal costs. The opposite situation of under-consumption during summer season when reservoir levels are relatively high could lead to very low market price since the value of hydro power production depends on its opportunity cost.

Demands could respond to price of electricity in the market to consume during low price hours as opposed to high price hours. Alternatively, response from demand could also be used to provide ancillary services to network operation such as frequency response, voltage and reactive power control, black start capability, voluntary load shedding etc. Such programs involving control of demand-side have historically been utilized but limited to large industrial consumers. With the roll out of smart meters, greater real-time control of domestic consumers' consumption could also be achieved. This could result in greater demand side participation in electricity markets possibly leading to more efficient use of generation resources while also reducing the stress on transmission network during peak consumption periods. The state of demand response in two select electricity markets is described in the following section.

### 2.3.1 Nordic Electricity Market

The Nordic physical markets provide opportunities for price dependent demand to compete directly with price dependent generation. This is especially the case with large scale industrial consumers who have the flexibility to bid for energy directly on the market on an hourly basis and to adjust their consumption in order to prevent being exposed to very high prices. When it comes to small and medium sized consumers, there is a plan to move towards a common retail electricity market with the Nordic region [23] that offers the option of variable retail pricing for consumers directly based on the wholesale price of electricity. In this regard, the installation of smart metering systems has been adapted [24] to measure real-time consumption pattern of domestic and commercial consumers of electricity.

There are notable challenges that exist for domestic consumer participation in the Nordic electricity markets [25]. Though an aggregator agent could be a legal entity in current Nordic day-ahead, intra-day and financial electricity markets, barriers arise when the aggregator would want to participate in the regulating power market. This is due to the fact that aggregator would need to assume the role of a balance responsible party (BRP) in order to participate in RPM, or contract with another BRP. There could be further limitations due to the rules and regulation regarding aggregation of demand in general and also, regarding a new market player assuming the role of a BRP. Another barrier that could hinder the participation of an aggregator is the minimum bid volume requirement by the TSO in RPM, which is 5 MW. This could prove to be a large volume for aggregators, especially in bidding areas with surplus production resources.

### 2.3.2 PJM Electricity Market

Pennsylvania-Jersey-Maryland Interconnection (PJM) is a regional transmission organization that operates the transmission grid and power markets for 13 eastern states and the District of Columbia in the United States. End-users can participate in PJM's day-ahead energy, capacity, reserves and regulation markets by reducing their demand for electricity [26]. Currently, the mechanism provided through demand response programs only attempt to replicate electricity market price signals instead of exposing them directly to end-users. This is done through curtailment service providers (CSP) who function similar to aggregator agents described previously. Specifically, the role of CSP is defined by PJM as: "*the entity responsible for demand response activity for electricity consumers in the PJM wholesale markets.*" A CSP may be a company that solely focuses on a customer's demand response capabilities, a local electricity utility, an energy service company or other type of company that offers these services. The CSP identifies demand response opportunities for customers and implements the necessary equipment, operational processes and/or systems to enable demand response both at the customer's facility and directly into the appropriate wholesale market. This requires the CSP to have appropriate operational infrastructure and a full understanding of all the wholesale market rules and operational procedures.

Some barriers in PJM market [27] that limits customer exposure to wholesale electricity prices could be accounted for due to the inadequate metering infrastructure, lack of jurisdictional clarity among regulatory authorities, lack of clear business rules etc. Furthermore, retail prices are set by regional authorities whose operations are decoupled from federal agencies.

## 2.4 Demand Response with future Electric Vehicles

Electricity markets were typically designed keeping in mind the operational characteristics of large, conventional production units. The structural and operational rules of electricity markets are continuously being adapted to changes that are occurring due to the pro-active environmental policies in the energy sector [28]. In line with these policies, electricity generation from renewable energy sources has received much focus in the recent past and is only expected to increase in the coming decades as reported by the International Energy Agency in [29]. Most of the renewable resources are intermittent in nature thereby giving rise to limited control over power generation. To maintain energy balance within the power system at all instances, it could become imperative to have controllability from other resources, which could be either non-renewable energy sources from the generation side, or control of resources on the demand side. Using more fossil fuel for power generation would defeat the purpose of integrating renewable energy resources into the power system.

With the introduction of smart metering systems at households and integration of information and communication technologies (ICT) with power system components, potential for control of virtually any demand arises. This means that even the lowest power consuming devices within households could be collectively controlled to provide services during power system operation. Many such programs delving into the control of household appliances have been launched and are being researched upon currently. It is imperative to understand the implications of investing in ICT and smart meters for end consumer demand control. The main question of whether demand control on small consumer level would benefit them in any way would need to be answered. A starting point would be to categorically observe the effects of demand control on consumers. Two categories that could have a direct effect are:

- Social effects- include the behavioral changes needed to be adopted by consumers to perform demand control, consumer feeling of performing a common good by promoting and supporting environmentally friendly resources and participating in programs that could prove to be good for the society in general.

- Economic effects- the customers would need to know how demand response programs would affect their electricity bills. Investment in smart meters could result in better awareness for the consumers on their consumption patterns that could, in the long term, result in overall energy demand reduction. But what would the effects be in the short term? With greater control and short term response programs, could active consumers gain greater savings in their monthly electricity bills? This would require further research to study the system level impacts of demand response on electricity markets and corresponding changes in price levels within the markets. These studies should take into account the characteristics of different classes of demands in order for them to be controlled in an effective manner. Such studies could also shine light on how demand response could affect other actors within the market framework.

Electrification within the transportation sector is considered to provide good opportunities for demand control in future power systems [30]. With battery energy storage systems, EVs provide flexibility regarding the sources of electrical energy for charging. Hence, if global policies are driven towards tapping renewable resources such as wind, solar, biomass, biogas, wave, tidal for power production, then power sources with lower carbon footprint could be used to charge the vehicles. With battery systems in EVs, greater flexibility could be achieved by storing renewable energy when it is available, and then re-using this energy during times of higher power imbalance. Hence, EVs could also be utilized to offset some of the intermittency in power production from renewable sources.

### 2.4.1 Classification of Electric Vehicles

Internal combustion engines (ICE) have been the heart of the automotive industry around the globe for over a century. The drawback of ICE is that they have predominantly used fossil fuels as an energy source. More recently, electric vehicles are being introduced by auto makers as an environment friendly alternative to ICEs run on petrol or diesel. In general, electric vehicles consist of a battery for energy storage, an electric machine for propulsion, a power electronic control system and a mechanical transmission system. Based on the configuration of these subsystems, electric vehicles could be classified into three main types as described below [31]. It is to be noted that the term 'EV' in this thesis refers to those vehicles whose batteries could directly charge from the electricity network and/or discharge into it.

1. *Hybrid Electric Vehicle* (HEV)- employ a traditional ICE engine supplemented by an electric motor and battery in order to increase the overall fuel efficiency as shown in Figure 2.12. Using the electric motor reduces idling of the car and enhances the vehicle's starting and accelerating abilities. This is advantageous for city driving that requires considerable stop-start-go cycles. It is to be noted that both the ICE and the electric motor could be use to drive the transmission system that in turn drives the wheels of the vehicle. At lower driving speeds, the electric motor usually drives the vehicles thereby reducing emissions, while at higher speeds the ICE is generally used. The battery in this type of EV is not recharged from the electric grid but from the combustion engine and regenerative braking. This limits the choice for battery charging source as compared with other types of EVs.

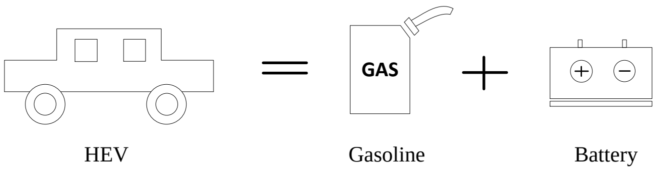


Figure 2.12: Hybrid electric vehicle

2. *Plug-in Hybrid Electric Vehicle* (PHEV)- is similar to the HEV as it uses two

power sources to propel the vehicle. However, the battery capacity of the PHEV is relatively higher with an added advantage that the battery could be connected and directly charged from an electricity outlet. This is shown in Figure 2.13. In addition, the battery could also be charged by using the combustion engine and regenerative breaking, similar to an HEV. With an increase in battery capacity, the PHEV could be used to an increasing degree to drive the vehicle and therefore increase the overall fuel efficiency of the vehicle when compared to the HEV or conventional ICE vehicle. In the near future, other alternative fuel vehicles using biogas, propane gas, hydrogen gas, etc. may become more prominent drivers of combustion engines. Alternatively, ICEs could be completely replaced by hydrogen fuel cells [32] that could, in turn, charge the batteries and drive the electric motors.

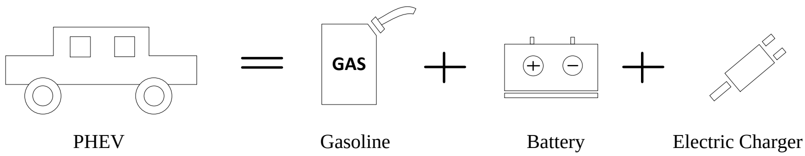


Figure 2.13: Plug-in hybrid electric vehicle

3. *Battery Electric Vehicle* (BEV)- are completely electric. Their propulsion is solely due to the functioning of an electric motor powered by a battery. The battery could be charged from an electricity outlet or regenerative breaking and has a capacity that is significantly larger than that of a PHEV or HEV. These types of vehicles are also referred to as plug-in electric vehicles (PEV). A representation of BEV is shown in Figure 2.14.

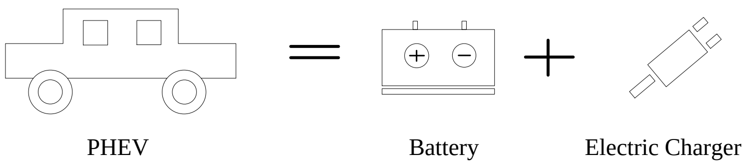


Figure 2.14: Battery electric vehicle

### 2.4.2 EV Aggregator

Most of the small and medium level consumers do not have a means to directly trade in electricity markets. In order to trade their flexibility, they would require the services of an aggregator agent that gather the flexibility offered by many consumers and pools in active demand capacity to be traded as a single resource. Example of loads that could be aggregated include: fans, electric cooling and heating, electric boilers, refrigerators etc. The aggregator could also generate agreements with consumers to adjust their energy consumption at moment's notice. A dedicated aggregator for trading flexibilities offered by EVs is the 'EV aggregator'. Within the context of electrical energy markets, the functions of the EV aggregator are similar to that of an electricity retailer. Hence, its interaction with other market participants could be described using Figure 2.15.

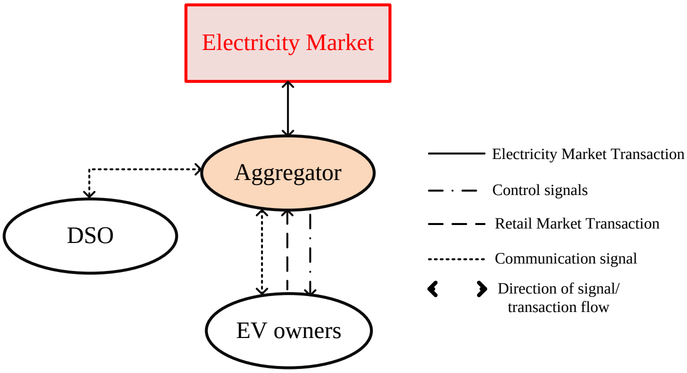


Figure 2.15: Overview of aggregator and its interaction in the physical markets

However, there could be some additional functions that need to be accommodated in order to include the concept of aggregator more efficiently within the electricity market [4]. Some of these could be listed as follows:

i There should be necessary communication infrastructure in place for the aggregator to obtain near real-time electricity consumption measurement, vehicle battery state and consumption needs of EV owners [33].

ii There should be a mechanism in place for the control of EV owner batteries. The batteries could be controlled directly by the aggregator with energy schedule validation by the DSO if the necessary automatic control infrastructure is established and market and power system operational rules permit the same. If the rules impose separation of the operational aspect and business aspect of the aggregator, then it could be possible for the DSO to take over the EV battery control function based on the energy scheduling plan communicated to the DSO by the aggregator [4].

iii It might become necessary to introduce shorter time periods of around 30 minutes or less between market closure and operating hour in order to reduce forecast errors by the aggregator [34].

iv For higher participation from small consumers, it could become essential to reduce minimum bid size in the market to values lower than 1 MW [34].

In this thesis, points (i) and (ii) are assumed to be available within both the joint scheduling and aggregator scheduling methods. It is also possible to incorporate points (iii) within the DAM market model by modifying the time resolution for scheduling by the aggregator and (iv) could be incorporated within RPM model by reducing the minimum bid size to be submitted by the aggregator to the market.

## 2.5 Summary

In this chapter, an introduction was provided to the Nordic electricity market along with a brief description of the physical and financial electricity markets. An overview of DSM along with its classification was also described with greater emphasis on DR. The concept of DR in the current market context was presented along with its extension to small consumer with new types of load from EV batteries and a motivation for the involvement of an aggregator agent.

# Chapter 3

# EV Energy Scheduling for the Day-ahead Market

*This chapter describes the model of an EV aggregator for participation in the day-ahead electricity market. The modeling is done by accumulating each of the individual vehicle batteries and treating it as a single large battery. The charging and discharging of this battery is then scheduled based on the traveling needs of the EV owners determined by an aggregated driving profile and the cumulative energy needs of individual batteries over the optimization horizon. Two methods to scheduling the vehicles under different day-ahead electricity market paradigms are proposed, which are subsequently used to observe the effects of introducing flexible scheduling of EVs within an IEEE test system and a Nordic test system.*

## 3.1 Review of EV aggregator in Day-ahead Market

With the expected mass adoption of EVs in the coming decades as reported by the IEA in [35], the increase in total electrical load in a system can be significant if the charging of EVs is uncontrolled [36]. To reduce the impacts of such an increase in EV demand, certain measures of control and coordination could become necessary. Charging strategies of EVs based on real-time price have been discussed in e.g., [37]–[39] and the charging of EVs can be scheduled and coordinated by an aggregator agent during periods of low electricity price as shown in [8]. In these works, the EVs are considered as price-takers in electricity markets, i.e., having no influence on the price determination. However, large fleets of EVs could result in changes to the shape of the daily load curve appearing in the electricity market which could in turn influence the level of market price.

A locational marginal price-based impact assessment has been done in [40] to show the effects of controlled and uncontrolled EV charging on the market price. However, it is necessary to observe these effects in a pool-based electricity market setup such as the Nordic electricity power exchange Nord Pool Spot [41]. In such a setup, the charging schedule of the EVs would need to be submitted to the market by an aggregator agent or electricity retailer. Hence, the scheduling of EV charging is performed before the scheduling of the generators. This market structure is implemented in this chapter using the proposed *aggregator scheduling method*. Furthermore, with adequate infrastructure for control and communication in place, the market can advance to a state where, the individual EV owners can directly interact with it, thereby, eliminating errors that arise due to scheduling of EV charging by the aggregator. This idea is implemented using the proposed *joint scheduling method*.

In this chapter, two methods for incorporating EV aggregator and their charge scheduling in day-ahead electricity markets have been developed and described. The EV aggregator is considered to be a price maker and would have a role in the determination of outcome of electricity price. In the joint scheduling method (JSM), EV energy is scheduled simultaneously with the generation units- the objective function being minimization of total generation cost. In the aggregator scheduling method (ASM), EV energy is first scheduled independently by an aggregator agent based on the estimated electricity market price. The charging schedule, which represents the EV energy demand, is submitted to the market in the same way as other conventional loads. In so modeling EV charging energy, the effects of EV energy demand on electricity market price will be assessed and compared among cases with and without EVs, as well as among cases with different scheduling methods.

It should be noted that while EVs can provide reserve capacity and energy back to the grid (known as vehicle-to-grid service) as considered by many recent studies such as [42], [43], in this chapter, we focus only on the charging of EVs from the grid.

## 3.2 Incorporating EV Aggregator in Market Model

In this section, two developed methods that incorporate EV energy scheduling in day-ahead market are described.

### 3.2.1 Joint Scheduling Method

In JSM, the EV energy scheduling is considered to be performed by a central entity like a system operator that also plans for the dispatch of the generators. The central operator is assumed to receive data related to the generators and EV batteries. The operator could then schedule both the generators and the EV charging energy demand by minimizing the total cost of generation. In a scenario where advanced methods of communication and control are feasible, individual EV owners could directly interact with the market by submitting the necessary EV data. In this scheduling method, the central operator is assumed to receive the following three sets of information:

1. Generator costs along with its technical constraints
2. Daily EV driving energy requirements, driving pattern data and aggregated EV battery energy limits.
3. Hourly conventional load data, which represents the inflexible demand data.

Using these three sets of information, the market model jointly schedules the generators and EV charging demand to minimize the total generation cost within a unit commitment framework [44]. This is shown in Figure 3.1.

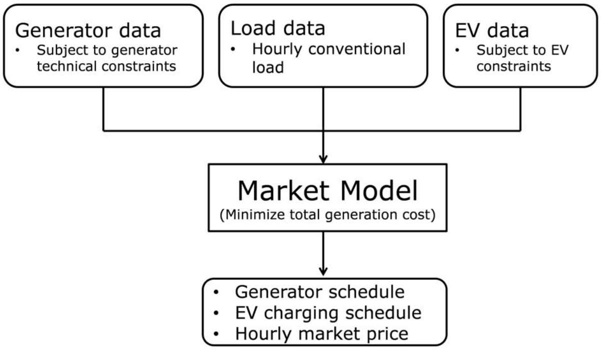


Figure 3.1: Overview of JSM

The generators are assumed to bid their true marginal cost of generating electricity and the market is settled with the minimum generation cost objective [45]. Demand, except that of EVs, is considered to be perfectly forecasted a priori, and is fixed for each hour.

The objective function of the market model is to minimize the total cost of generation to supply the load over the time horizon $T$. This cost also includes the start-up cost of generating units. This is formulated as shown in (3.1).

$$Minimize \quad DAMC = \sum_{m \in M} \sum_{t \in T} (VC_m p_{m,t} + y_{m,t} SC_m) \tag{3.1}$$

where, $DAMC$ is the total cost of scheduling the generators in the day-ahead market, $VC_m$ is the variable cost of power production of generating unit $m$ and $p_{m,t}$ is the power produced by unit $m$ at time $t$, $y_{m,t}$ is a binary variable indicating the starting up of unit $m$ at time $t$ and $SC_m$ is the start-up cost of unit $m$.

The objective function $DAMC$ in JSM is subject to constraints (3.2)- (3.15) imposed by the generating units, (3.16)- (3.19) imposed by the aggregated EV batteries and power balance constraint (3.20).

#### 3.2.1.1 Generating Unit Constraints

The generating units should generate power greater than their minimum limits at all times $t$ as shown in (3.2). The decision of whether the generating unit generates power at time $t$ is taken using a binary variable $v_{m,t}$. The value of $v_{m,t} = 1$ indicates that the unit $m$ is committed to generate power at time $t$ whereas a value of $v_{m,t} = 0$ indicates that the unit $m$ is de-committed from generating power at time $t$.

$$p_{m,t} \geq v_{m,t} P_m^{min}; \quad \forall m \in MG, t \in T \tag{3.2}$$

The constraints for maximum available power from the generating unit and its ramp rate limit are formulated as shown in (3.3) and (3.4). These constraints account for the generating unit capacity, start-up ramp rate limit, shut-down ramp rate limit and the ramp-up limit of the unit. The maximum available output from the generator becomes zero when $v_{m,t} = 0$, i.e., the unit is offline.

$$p_{m,t} \leq P_m^{max}[v_{m,t} - z_{m,t+1}] + z_{m,t+1} SD_m; \quad \forall m \in MG, t \in T \tag{3.3}$$

$$p_{m,t} - p_{m,t-1} \leq RU_m v_{m,t-1} + SU_m y_{m,t}; \quad \forall m \in MG, t \in T \tag{3.4}$$

The constraint in (3.5) enforces the ramp-down rate limit and the shut-down ramp rate limit for the unit.

$$p_{m,t-1} - p_{m,t} \leq RD_m v_{m,t} + SD_m z_{m,t}; \quad \forall m \in MG, t \in T \tag{3.5}$$

Expressions (3.6)- (3.9) impose minimum up time constraints on the generating units.

$$\sum_{t=1}^{GU_m} [1 - v_{m,t}] = 0; \quad \forall m \in MG \tag{3.6}$$

$$GU_m = Min[T, (UT_m - U_m^0)V_m^0] \tag{3.7}$$

$$\sum_{k=t}^{t+UT_m-1} v_{m,k} \geq UT_m y_{m,t}; \quad \forall m \in MG, \;\; t \in \{GU_m + 1, ..., T - UT_m + 1\} \tag{3.8}$$

$$\sum_{k=t}^{T} [v_{m,k} - y_{m,t}] \geq 0; \quad \forall m \in MG, \;\; t \in \{T - UT_m + 2, ..., T\} \tag{3.9}$$

Constraint (3.6) accounts for the initial status of the units. $GU_m$ is the total number of initial periods during which the unit $m$ must be online and is calculated as shown in (3.7). The constraint in (3.8) ensures that the minimum up time constraint during all the possible sets of $UT_m$ consecutive periods is satisfied for each period following $GU_m$. If a generating unit is started up in one of the last $UT_m - 1$ periods, (3.9) ensures that it remains online during the rest of the periods until $t = \{T\}$.

The set of expressions in (3.10) - (3.13) impose the minimum down time constraints on the generating units. These are similar to the minimum up time constraints with the difference that $1 - v_{m,t}$, $y_{m,t}$, $UT_m$, $U_m^0$ in (3.6)-(3.9) are replace by $v_{m,t}$, $z_{m,t}$, $DT_m$, $S_m^0$ in (3.10)-(3.13), respectively.

$$\sum_{t=1}^{GD_m} v_{m,t} = 0; \quad \forall m \in MG \tag{3.10}$$

$$GD_m = Min[T, (DT_m - S_m^0)[1 - V_m^0]] \tag{3.11}$$

$$\sum_{k=t}^{t+DT_m-1} [1 - v_{m,k}] \geq DT_m z_{m,t}; \quad \forall m \in MG, \ \ t \in \{GD_m + 1, ..., T - DT_m + 1\} \tag{3.12}$$

$$\sum_{k=t}^{T} [1 - v_{m,k} - z_{m,t}] \geq 0; \quad \forall m \in MG, \ \ t \in \{T - DT_m + 2, ..., T\} \tag{3.13}$$

The constraints in (3.14) and (3.15) are necessary to model the start-up and shut-down status of the units and avoid simultaneous commitment and decommitment of a unit.

$$y_{m,t} - z_{m,t} = v_{m,t} - v_{m,t-1}; \quad \forall m \in MG, t \in T \tag{3.14}$$

$$y_{m,t} + z_{m,t} \leq 1; \quad \forall m \in MG, t \in T \tag{3.15}$$

#### 3.2.1.2 EV Battery Constraints

In the developed mathematical model, the individual batteries are assumed to be aggregated and treated as a single battery. The constraints essentially reflect the charging and discharging operation of the aggregated vehicle battery while accounting for the traveling energy needs of EV owners based on their aggregated driving pattern. It is further assumed that the vehicles are available to the grid for charging at all times when they are not traveling.

**3.2.1.2.1 Minimum Energy Requirement:** It is considered that the EV owner gives information about how much travel is intended for the next day in kilometers. The aggregator/central operator could then estimate the charging energy required based on the characteristics of the EVs. The aggregator/central operator would schedule only that amount of charging energy necessary over its initial state of energy as shown in (3.16).

$$SOC^{ini} + \sum_{t=1}^{T} E_t \geq SOC^{min} + \sum_{t=1}^{T} E_t^{next} \tag{3.16}$$

Where, $E_t^{next}$ is the energy required by the EV for next day travel during hour $t \in T$, $T$ is the optimization period length, $SOC^{ini}$ is the initial state of energy in the battery and $SOC^{min}$ is the minimum energy requirement imposed by the EV owner on the battery.

**3.2.1.2.2 Charging Period Limit:** It is assumed that the EV owner provides information about the time and duration of traveling intended for the upcoming day. The aggregator/central operator could use the provided driving information to generate an aggregated driving profile of its EV customers that would, in turn, provide the unavailability of the vehicles. The aggregator/central operator needs to schedule the charging of the EV in such a way that the battery is charged during hours $tf = (1, 2, ..., t-1)$ before it travels during hour for all values of $t \in T$.

$$\sum_{tf=1}^{t-1} E_{tf} - E_{tf}^{next} \geq E_t^{next} \tag{3.17}$$

**3.2.1.2.3 Battery State:** Charging and discharging of the battery during consecutive hours results in a change in its energy level. This is formulated as:

$$SOC_t = \begin{cases} SOC^{ini} + E_t - E_t^{next} & \forall t \in \{1\} \\ SOC_{t-1} + E_t - E_t^{next} & \forall t \in \{2, 3..., T\} \end{cases} \tag{3.18}$$

**3.2.1.2.4 Battery Energy Limits:** The energy state in the battery should not deviate from its minimum and maximum limits, $SOC^{min}$ and $SOC^{max}$, respectively.

$$SOC^{min} \leq SOC_t \leq SOC^{max}; \;\; \forall t \in (1, 2, ..., T) \tag{3.19}$$

#### 3.2.1.3 Power Balance Constraint

The power balance between generation and supply must be maintained. This is mathematically formulated as shown in (3.20).

$$\sum_m p_{m,t} = C_t^L + E_t; \tag{3.20}$$

The total demand consists of the conventional demand $C_t^L$ and the demand from the EV charging energy $E_t$. The EV charging energy is an endogenous variable when EV scheduling is performed using the JSM. However, it is provided as an input parameter to the DAM model when the ASM is utilized.

### 3.2.2 Aggregator Scheduling Method

In ASM, the EV aggregator is assumed to function similar to an electricity retailer in the market. The aggregator plans for DAM participation by independently scheduling EV energy based on its objective of minimizing the total cost of charging. For the scheduling, the EV aggregator is assumed to have the following three sets of information:

1. Daily EV driving energy requirements, driving pattern data and aggregated EV battery energy limits.
2. Hourly conventional load data, which represents the inflexible demand from all other loads other than EV demand.
3. Estimated supply function.

Using the above sets of data, the aggregator schedules the charging energy of EVs such that the total cost of charging is minimized as shown in Figure 3.2.

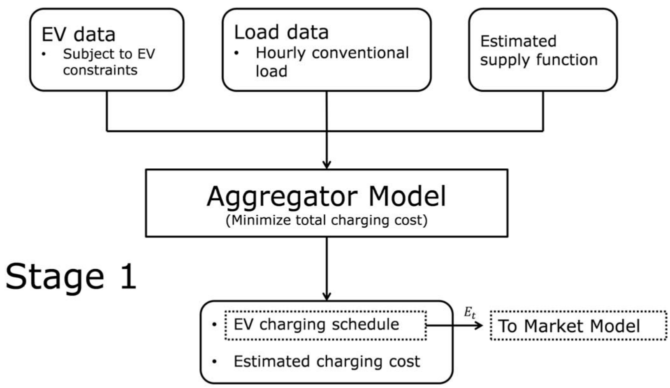


Figure 3.2: Overview of ASM:Stage 1

#### 3.2.2.1 EV Aggregator Model

The EV aggregator ensures that the charging and discharging events of the vehicle's aggregated battery is scheduled considering the unavailability of EVs due to driving needs. Batteries within electric vehicles are essentially loads that are required to be charged with sufficient energy to ensure smooth operation of the vehicle according to the driver's needs. Hence, it could be reasonable to assume that the main position held by the EV aggregator is as a consumption entity within the electricity market. Considering such a stance, the objective function of the aggregator would then be to make sure that the cost from energy purchased for charging of all the EVs is minimized while accounting for the driving needs of the EVs. Due to its participation in the day-ahead market, the charging energy price would depend on the market price of electricity. If hourly charging costs are directly imposed on the EV owners, the objective function could then be represented using (3.21).

$$Minimize \quad ACC = \sum_{t=1}^{T} \hat{\pi}_t^s E_t \tag{3.21}$$

where, $\hat{\pi}_t^m$ is the day-ahead price forecasted by the EV aggregator at time $t$ using the estimated supply function. Depending on the structure and organization of the day-ahead market, it is possible that the charging price used by the EV aggregator is either an endogenous variable or an exogenous parameter. If the market structure is such that it requires the aggregator to plan the hourly charging needs before submitting its energy requirements to the market, then the electricity price would need to be estimated and it would identify itself as an exogenous parameter within the aggregator model.

The objective function in (3.21) is subject to constraints imposed by the needs of vehicle owners along with the technical limitations of the battery as described in (3.16)-(3.19).

The estimated supply function gives an approximation of how the market price varies with changes in total demand. This function is important to identify the effect of total EV demand on the market price when it is no longer a price taker. The estimated charging price is modeled to be dependent on the total demand within the system as is shown in (3.22).

$$\hat{\pi}_t^s = f(C_t^L, E_t) \tag{3.22}$$

Where $CL_t$ is the total forecasted conventional load and $E_t$ is the EV charging energy to be scheduled. The estimated function can also be obtained from historical data on price and demand level cleared in the market.

#### 3.2.2.2 Market Model

The EV charging schedule $E_t$ from ASM:Stage-1 is then provided to the market model in ASM:Stage-2 where the generators are scheduled to meet the total demand from the conventional load and the scheduled EV energy in a way so as to minimize the total generation cost. This is shown in Figure 3.3.

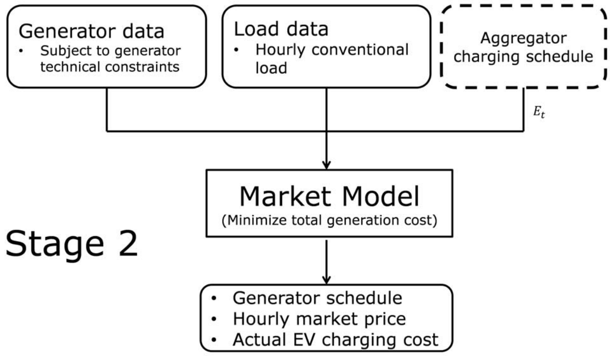


Figure 3.3: Overview of ASM:Stage-2

The objective function of market model in ASM is described by $DAMC$ in (3.1) and is subject to constraints (3.2)- (3.15) imposed by the generating units and the power balance constraint (3.20).

## 3.3 Case Study

The methods described in the previous section are applied on a modified IEEE 30-bus test system and a Nordic test system. The input data related to EVs used for both the JSM and ASM case studies were obtained from a report published by the *Grid for Vehicles* (G4V) project under the European commission's $7^{th}$ framework programme [48], and are shown in Figure 3.4 and Table 3.1, respectively.

The driving pattern shown in Figure 3.4 is dependent on vehicle users and it is reasonable to assume that the driving behavior would not change drastically with the introduction of EVs. Hence, the conventional vehicle user behavior is considered to be representative of the expected EV user behavior.

The battery capacity and energy consumption in Table 3.1 are calculated based on the expected composition, at high penetration levels, of BEVs and PHEVs, and represent a weighted average value.

The battery charging and discharging characteristics are highly non-linear and depend

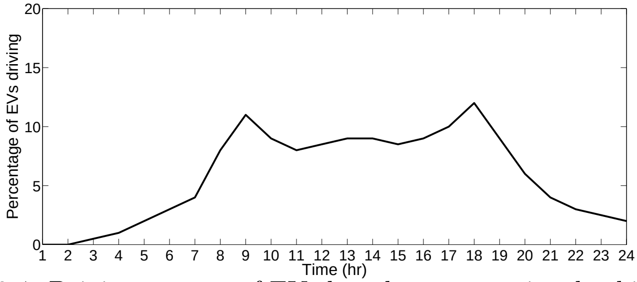

Figure 3.4: Driving pattern of EVs based on conventional vehicle data

Table 3.1: EV related parameter values

| | |
|---|---|
| Battery Capacity | 24 kWh |
| Energy Consumption (per km) | 0.192 kWh/km |
| Average Distance Traveled | 40 km/day |
| Energy Consumption (per day) | 7.68 kWh/day |
| Charging Power Available | 3.68 kWh/h |

on the type of battery. Li-ion batteries are considered here as they appear to be the most promising type for EV application [46]. Their charging curve indicates that the charging power is nearly constant within a certain range of their SOC [47]. Hence, the values of $SOC^{min}$ and $SOC^{max}$ are fixed at 20% and 85% of the battery capacity for all simulations.

### 3.3.1 IEEE 30-bus Test System

The presented JSM and ASM have been applied to a modified IEEE 30-bus test system [49] to observe the effects of EV aggregator demand scheduling on the price of electricity. The test system consists of nine generating units that are subjected to the following general technical constraints [44]: minimum and maximum generation limit, minimum up and down time, up/down ramp rate limits and start-up/shut-down ramp limits.

The penetration level of EVs is defined as the ratio of total number of EVs to the total number of vehicles in the system. An estimated total of 170000 EVs would, in addition to the conventional load, result in energy requirements that would lead to the flattening of the daily load curve at a level corresponding to the peak demand. Since, information about vehicles in this test system is not readily available; the above estimate is referenced to as the total number of vehicles in the system.

In ASM, the aggregator is considered to make use of the estimated supply function described in (3.23) to evaluate the effect of EV load on the market price and schedule the charging accordingly.

$$\hat{\pi}_t^s = a_1(C_t^L + E_t) + a_0 \tag{3.23}$$

where, $a_1$ and $a_0$ are constant coefficients. The estimated supply function for this system is shown in Figure 3.5.

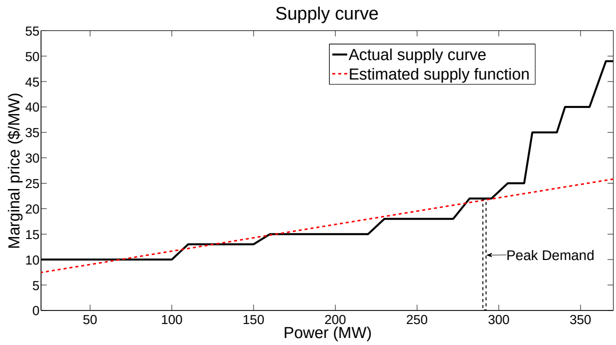


Figure 3.5: Supply curve for modified IEEE 30-bus system

#### 3.3.1.1 Fixed Period Charging

To obtain an idea of how the total load and market price will vary with the introduction of EVs when the market has limited (and/or indirect) control over the charging, a fixed period charging mechanism is described. A simple charging of EVs can be implemented by allowing their demand to be scheduled only during certain hours of the day (here, hours 1 to 6) when the conventional load is low. Figure 3.6 shows the variation of total hourly load at different levels of EV penetration and Figure 3.7 shows the variation of hourly market price with different levels of EV penetration within the system.

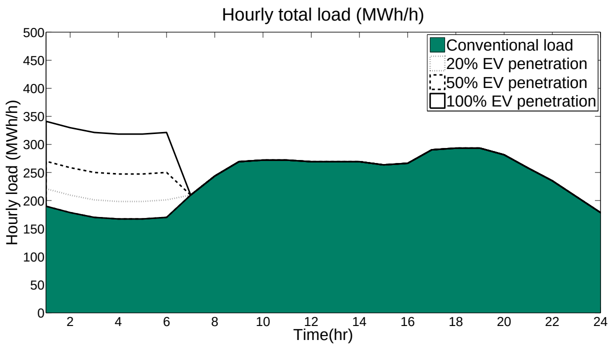


Figure 3.6: Fixed period charging result- total load

It can be observed from Figure 3.7 that at penetration levels of 20% and 50%, increase in market price is not significant indicating that even a simple charging mechanism could be effective in maintaining an acceptable increase in market price by the introduction of EVs. But at higher penetration levels, i.e., ¿ 50%, Figure 3.6 indicates that the total load

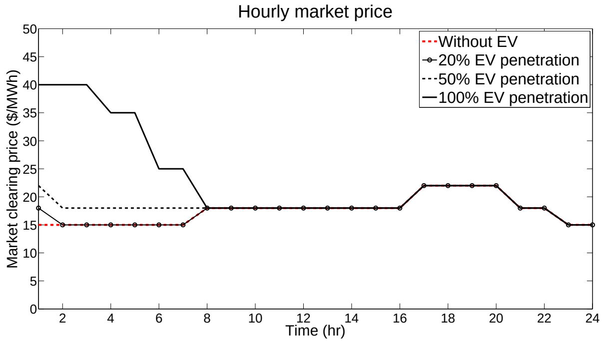


Figure 3.7: Fixed period charging result- market price

during early hours exceeds the peak demand due to conventional load alone (hour-18). The increase in market price can also be seen in Figure 3.7 as more expensive generators need to be scheduled to supply the additional EV load resulting in a market price as high as 40 \$/MWh during the first three hours.

#### 3.3.1.2 Joint Scheduling Method

The JSM is implemented for this test system and the resulting market price for various penetration levels of EVs is shown in Figure 3.8. Comparing Figure 3.7 and 3.8, it can be seen that at lower penetration levels of 20% and 50%, there is no significant difference in the increase of market price between fixed period charging and JSM. But, at higher penetration level of 100%, JSM results in a more uniform market price of 22 \$/MWh, indicating better utilization of generating resources.

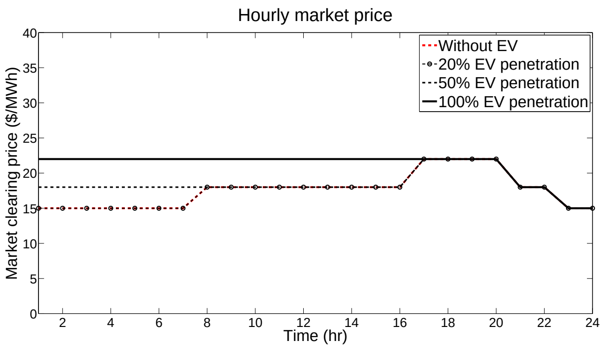


Figure 3.8: JSM result- market price at various EV penetration levels

Figure 3.9 shows the hourly total load at 100% EV penetration. It can be seen that the total load in the system does not exceed the peak load at hour 18 even at 100% EV penetration. This can be significant in systems that are stressed and might need network reinforcement in the case of fixed period charging, but the same can be avoided using JSM.

It is interesting to note that little or no charging takes place during the hours 23 and 24. This may be due to two reasons- one, the optimization horizon in the model is limited to 24 hours and two, the EV energy requirements need to be respected before their hour of travel.

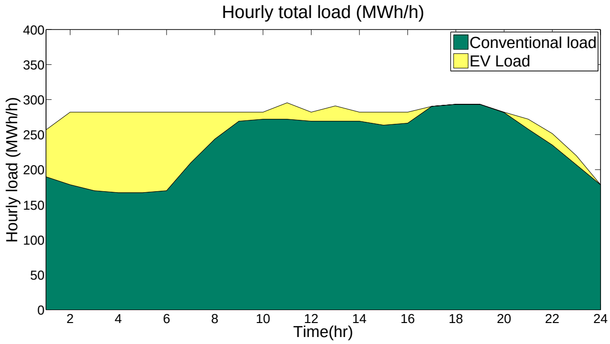


Figure 3.9: JSM result- system demand at zero and 100% EV penetration

#### 3.3.1.3 Aggregator Scheduling Method

The results obtained from this scheduling method are shown in Figure 3.10 for various EV penetration levels. Comparing Figure 3.7 and 3.10, it can be seen that at 20% penetration, the market price during the day increases similarly in both models. However, at 50% penetration level, the aggregator model results in an increase in market price by 4 $/MWh during hours 9 to 20. This could be attributed to the aggregator not being able to perfectly forecast the dependency of price on changes in demand. Since, forecasting brings about an error in the estimated price, the aggregator schedules higher or lower charging energy during an hour, depending on whether the demand dependency was underestimated or overestimated, respectively.

The hourly load result from ASM is compared with the result from JSM for 100% EV penetration and is shown in Figure 3.11. It can be seen that the error in estimation by ASM results in lower EV load to be scheduled between hours 2 to 7 when compared with the JSM. Due to this under-scheduling of EV load during the early hours, greater EV load is scheduled between hours 9 to 21.

The corresponding changes in market price can be seen in Figure 3.12. This price directly reflects the errors in forecasting by the aggregator on market price. It is lower by about 4 $/MWh during hours 2 to 7 but, consequently, increases by 4 $/MWh during the later hours 9 to 21 when compared to JSM results.

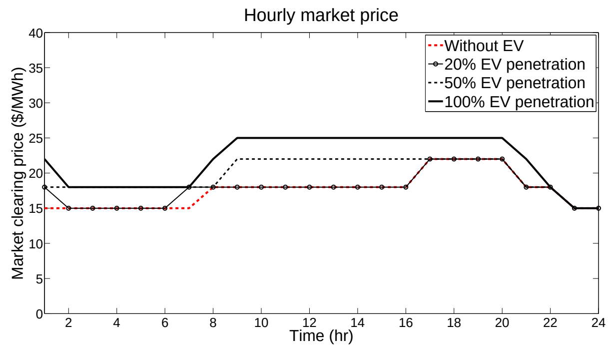


Figure 3.10: ASM result- market price at various EV penetration levels

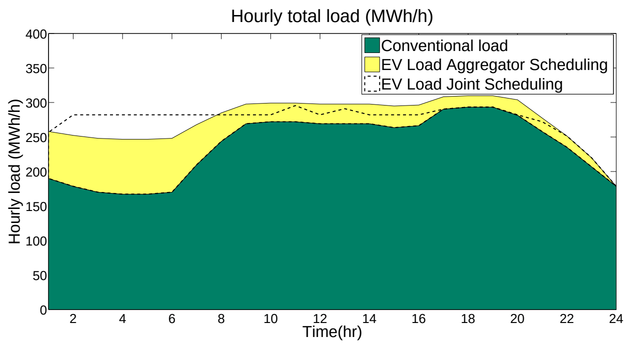


Figure 3.11: ASM and JSM comparison result- system demand at zero and 100 % EV penetration

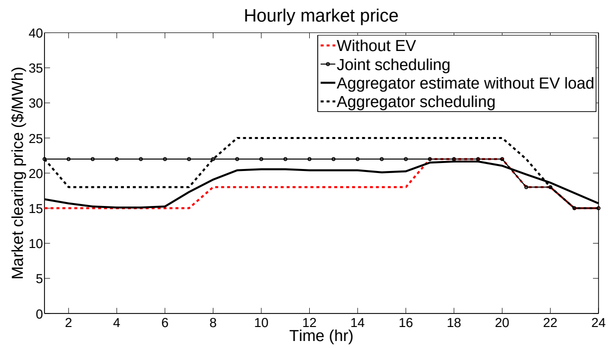


Figure 3.12: ASM and JSM comparison result- market price at zero and 100 % EV penetration

### 3.3.2 Nordic Test System

The proposed JSM is used to simulate the participation of EV charging in the Nordic day-ahead market called Elspot, which consists of five participating countries from the Nordic region, namely- Norway, Sweden, Finland and Denmark. Market players who want to trade electricity on the Elspot market must submit their sell offers and/or buy bids for every hour of trading to the market, no later than 12:00 hours, on the day before the power delivery. These bids are submitted via the internet to the website of Nord Pool Spot. The collected sell bids are cumulated in increasing order of price to form a supply curve and the buy bids are cumulated in decreasing order of price to form a demand curve- for every hour. The intersection of the two curves gives the market price of electricity for that hour. More information on the operation of Elspot can be found in [41].

Due to the physical restrictions imposed on energy trading by transmission lines, the Nordic electricity market area is divided into a number of bidding areas. The TSO decides on the criteria and number of bidding areas. Since, the operations of a TSO are generally limited to one country, a bidding area does not traverse political boundaries between countries in the Nordic region. Currently, Norway is split into 5 bidding areas- NO1 to NO5; Sweden into four- SE1 to SE4; Denmark into two- DK1 and DK2; and Finland into one- FI.

The total installed generating capacity in Nordic region is 96 GW. The share of total installed generation capacity based on the bidding areas in the Nordic region (excluding Estonia, Latvia and Lithuania) is shown in Figure 3.13 [50].

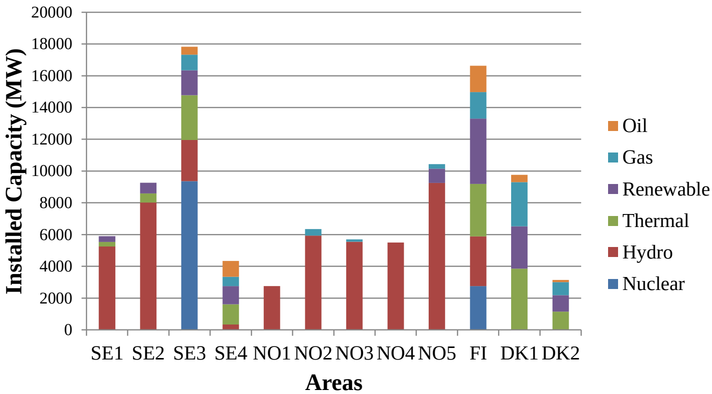


Figure 3.13: Generating capacity distribution by bidding area in the Nordic region

Installed generation capacity data for units greater than 100 MW for all four countries is obtained from [51], based on the type of generating technology. The variable cost of power generation based on different technologies in [52] is used and and scaled to reflect the average system prices in Nord Pool Spot for the year 2012 [53], after which the aggregated supply curve in the Nordic test system can be obtained as shown in Figure 3.14.

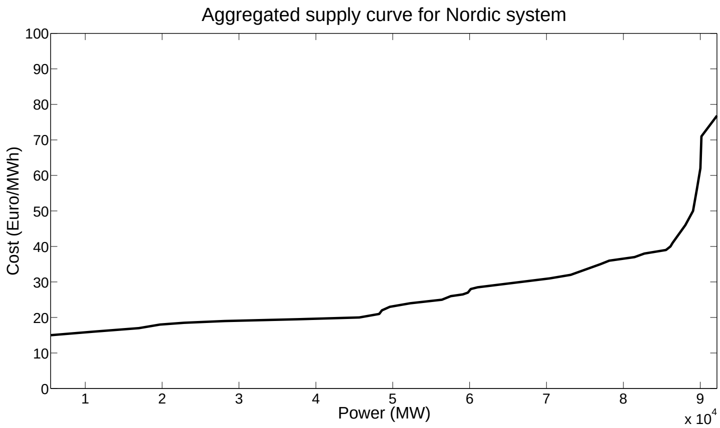


Figure 3.14: Supply curve in the Nordic test system

The aggregated supply curve is based on installed generation capacity in four countries- Norway, Sweden, Finland and Denmark. A normal market situation is considered, where, all the installed generation capacity is available. Two generation technologies that influence this assumption critically in the Nordic market are- hydro and nuclear power. With respect to hydro power, it reflects a situation when there is sufficient inflow to the hydro power station reservoirs in Norway and Sweden. This can further be classified as a normal winter that occurs every other year. This is in line with a study on vulnerabilities of the Nordic power system where, 90% hydro availability is assumed in Norway and Sweden during normal hydro conditions [54]. Similarly, due to the low probability of forced outages of nuclear power generation in Sweden and Finland, 100% availability is assumed.

The vehicle data required to simulate the participation of EVs in the Nordic market is based on statistics available for conventional fuel driven vehicles and is obtained from [55]–[58]. The resolution of this data currently available is for each county present in each of these countries. The total number of conventional vehicles in the Nordic area is found to be around 12.7 million. These are approximately segmented according to bidding areas and the resulting distribution is shown in Figure 3.15.

It is difficult to estimate the elasticity of conventional demand in the short-term since this elasticity would occur in special circumstances, where, the price of electricity is very high over a sustained period of time (days or weeks). Hence, the conventional demand is assumed to be inelastic as shown for the case of peak demand in Figure 3.14.

The impact of the assumptions made in this study on the final results and its analysis is optimistic, while at the same time, reflecting a highly expected market situation. It is imperative to mention that the simulation models are designed for a single auction market while the Nordic market is, in fact, a double auction market where a number of market players determine the outcome. A direct consequence of this may be a lower resulting market price due to better utilization of generating resources.

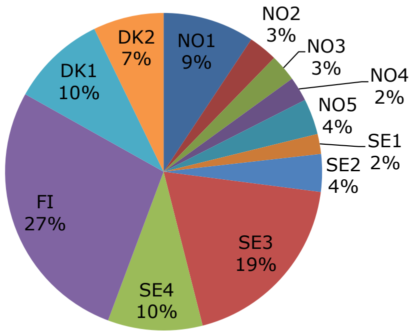


Figure 3.15: Conventional vehicles' distribution based on bidding areas

The external interconnection capacities between countries within and outside of the Nordic area are included as inelastic demand thereby representing an export scenario from the Nordic countries. This is indicative of an anticipated market situation, though, in reality, the complete transmission capacity may not be utilized.

The JSM will be applied to the following two cases of the Nordic market:

1. Unconstrained case: when the trading of electricity is not limited by the interconnection capacities between different bidding areas in the Nordic region.

2. Constrained case: trading of electricity is limited by the interconnection capacities between different bidding areas in the Nordic region, which are modeled based on the net transfer capacity (NTC) values [59].

Only the JSM is used for the case study of the Nordic market, because the ASM is heavily dependent on the accuracy of the estimated supply function given by 3.22. The accuracy of this function could be improved by modeling the price as a polynomial function of demand, although, by doing so, the complexity of the optimization function increases and the resulting model might not necessarily provide a solution. The consequence of such an assumption is the results being more optimistic, where the available generation and flexible demand are utilized more resourcefully.

#### 3.3.2.1 Unconstrained Case

Theoretically, if there were no upper limits on interconnection capacities, one supply and one demand curve would be used for the clearing of the whole Nordic day-ahead market. In a single auction market, it would translate into a single supply curve for the entire Nordic market. This would then be matched with the demand curve during that particular hour to obtain the market price for electricity.

The demand profile for this system was obtained using the data in [60] for a Tuesday during week 51 with an aggregated peak demand of 69 GW [50]. In such a context, if EVs are introduced into the system and their charging energy traded in the Nordic

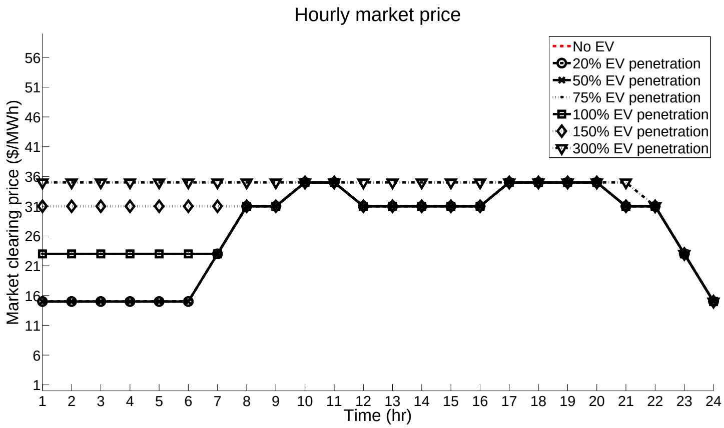


Figure 3.16: Unconstrained case result- changes in market price by the introduction of EVs

market as flexible demands, the corresponding changes to the electricity price in the day-ahead market, for various penetration levels of EVs, can be obtained as shown in Figure 3.16.

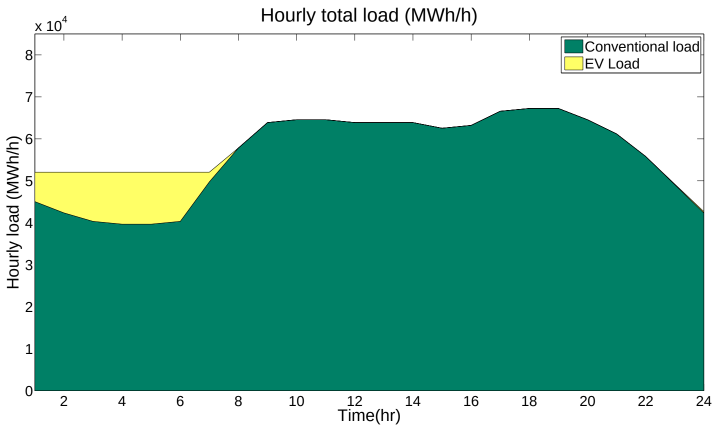


Figure 3.17: Unconstrained case result- total load at 100 % EV penetration

It can be observed that even if all the 12.7 million conventional vehicles were replaced by EVs, the market price would increase by 8 €/MWh during low demand periods. It would require an introduction of at least 37 million EVs before the system price during most hours corresponds to the peak load price of 35 €/MWh during hour 18. Hence, the Nordic market could be considered to be highly resilient towards the introduction of EVs. The changes in hourly total load and market price, with the introduction of 12.7 million EVs in the Nordic region, are shown in Fig. 3.17 and Fig. 3.18, respectively.

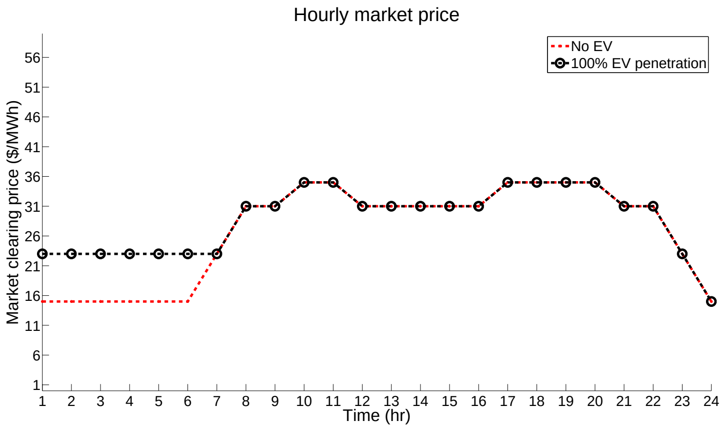


Figure 3.18: Unconstrained case result- market price at 100 % EV penetration

#### 3.3.2.2 Constrained Case

With interconnection capacities in place, area prices apply when power traded between at least two areas in the market exceeds the total available transmission capacity between those areas. The area market prices in the Nordic market for the constrained case are shown in Fig. 3.19. Y-axis denotes the area prices; x-axis denotes the 12 bidding areas and the colored bars from blue to red denote the 24 hours under consideration for each area.

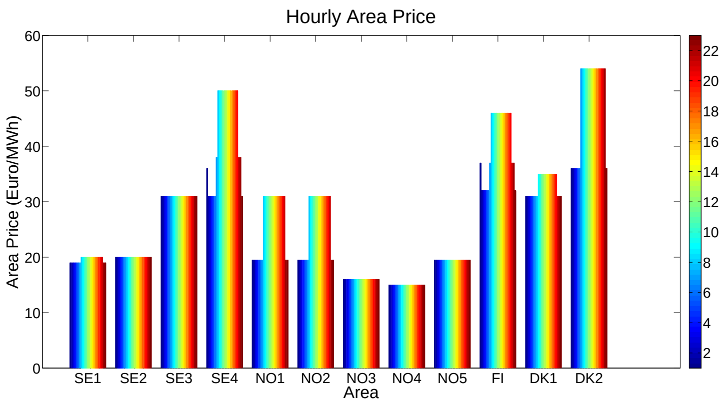


Figure 3.19: Constrained case result- area prices with only conventional load

It can be seen in Fig. 3.19 that areas FI, SE4 and DK2 already suffer from high prices compared to other areas primarily due to the dominant fossil fuel-based local generation. Prices in most of the areas are different indicating that the interconnections between these areas have been fully utilized. In areas NO1 and NO2, it can be observed that the prices during all of the 24 hours are the same indicating that the available transmission capacity is not completely utilized.

Extension of the model to include scheduling of EV charging results in area prices as shown in Fig. 3.20, for 100% penetration of EVs in the market. In hydro power dominated areas- SE1, SE2, NO1-NO5, it can be seen that the market price remains relatively the same during all hours even with a high penetration of EVs. It is also found that mainly two areas, namely- SE4 and DK2 are affected by the high levels of EV penetration. At 100% EV penetration level, the electricity price in DK2 increases to 54 €/MWh even during the low demand hours 1-7, whereas it increases to 38 €/MWh in SE4 during the same hours. Further introduction of EVs would result in a market price higher than 54 €/MWh in DK2 that corresponds to the price at peak demand with only conventional demand.

Area price for SE4 at different penetration levels is shown in Fig. 3.21. Similarly, for

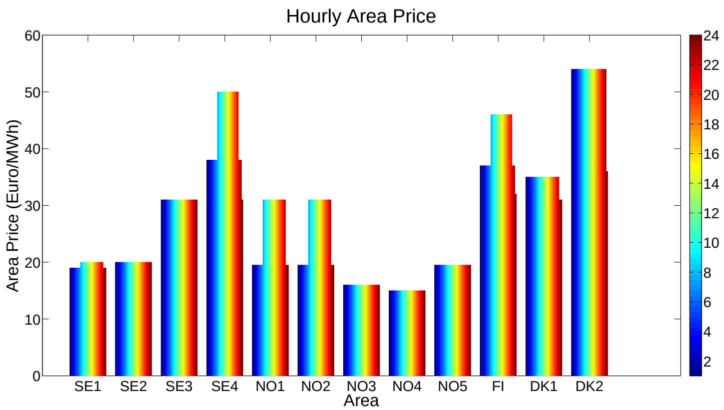


Figure 3.20: Constrained case result- area prices with 100 % EV penetration

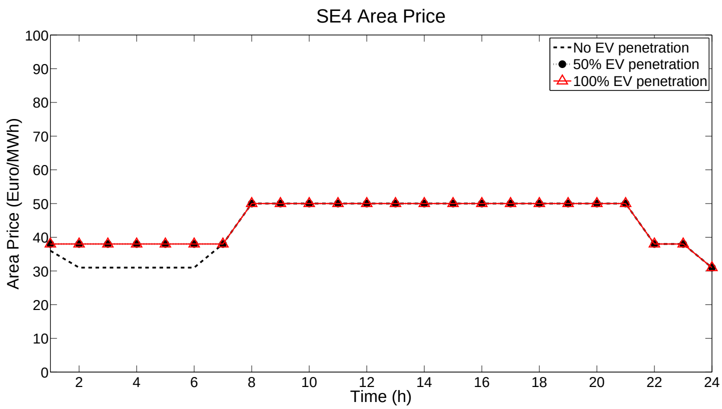


Figure 3.21: Constrained case result- SE4 area price at different EV penetration levels

the bidding area DK2, the area price at different penetration levels is shown in Fig. 3.22.

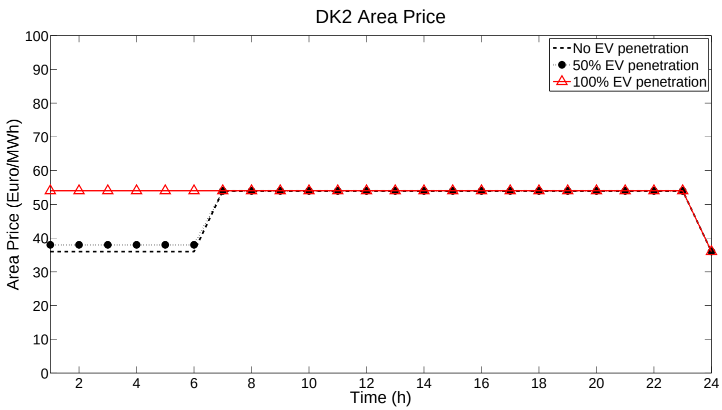


Figure 3.22: Constrained case result- DK2 area price at different EV penetration levels

It can be seen that the area prices in SE4 and DK2 increase with an increased penetration of EVs in the Nordic system. This may be attributed to a number of factors, for e.g., these two areas are dominated by thermal generators which are generally more expensive, capacity of transmission lines connecting them to generator surplus areas are insufficient and greater population in these areas account for relatively higher number of EVs being integrated at higher penetration levels.

## 3.4 Summary

In this chapter, joint scheduling and aggregator scheduling methods were proposed that could be used to evaluate the effects of EVs scheduling on the overall system load shape and the effects on electricity market price. JSM could prove useful in a market setup where there is a possibility to schedule both the generation and demand side resources; whereas ASM could be useful where individual market players would require performing their individual energy scheduling.

The two methods were applied to an IEEE 30-bus test system and a Nordic test system to find the effects of EV energy scheduling on market price of electricity. From the case study on the IEEE 30-bus test system, it was found that market integration of EVs might lead to an increase in market price at higher penetration levels using fixed period charging, at which point, advanced methods of scheduling of EV charging could become necessary. The proposed JSM may require changes in the operational structure of electricity markets, but the model could result in better utilization of resources as it simultaneously schedules both the generation and demand resources.

In the unconstrained case, the Nordic market was found to be highly resilient toward integration of EVs. Transmission network constraints, however, could directly influence the penetration level of the EVs that can be accommodated in the system before a significant increase in market price.

# Chapter 4

# EV Energy Scheduling for the Regulating Power Market

*This chapter describes an optimization model for scheduling energy by EV aggregator for its participation in the regulating power market. A market framework based on nodal pricing is assumed. A mechanism for clearing the market while considering the effect of power injection at nodes on transmission network losses is proposed. Finally, a case study on a Nordic 32-bus test system is performed and the results are presented.*

## 4.1 Review of EV aggregator in RPM

A recent trend in the electric power sector is the increasing penetration of wind power within the generation mix [50]. The uncertainty associated with increasing wind power and its forecast would require larger volumes of balancing power in these systems [61]. In the future, with increasing penetration levels and aggregation, EV batteries could have the potential to be charged during low demand periods of the day, when wind power production is high and provide power up regulation services during high demand periods of the day thus, offsetting the need for regulation from conventional generating units running on fossil fuels.

The dispatch of balancing resources in a power system is based on the imbalance between supply and demand during real-time operation, which is reflected by system frequency. From the beginning of 2013, three levels of frequency control are being employed in the Nordic power system [62]. Tertiary control or manual reserve resources are procured via bids in the regulating power market (RPM) and the lowest cost bids are normally activated when necessary. Such a procurement of balancing resources might not be the most effective since power losses in the system are not considered during activation [63] and the system might incur additional regulation costs. Hence, it is necessary to include the effect of transmission losses and network constraints while selecting the regulation bids.

In [64], a model for RPM based on incremental DCOPF considering marginal transmission loss is presented and it is shown that this approach could lead to a better utilization of reserves in RPM. The present chapter extends the application of this approach by further modeling the participation of possible demand-side flexibility from EVs in the future. A model of the RPM is proposed wherein the activation of regulating power resources is performed based on re-valued regulation price, reflecting the regulating power's contributions to active power losses in the network. The effect of changes in active power injection at various generator and EV buses on the transmission line limits are also modeled as constraints during the activation process. This approach is implemented within an ACOPF framework where the power flows and system loss can be precisely evaluated. Furthermore, demand-side participation by EVs in providing regulating power in the market is incorporated in the RPM model. A case study is carried out based on the proposed model using a modified Nordic 32-bus system. Results from the proposed market model will be compared with those of the current approach used in the Nordic RPM based on a merit list without loss consideration. Also, effects of EVs participation in regulating power market will be studied.

## 4.2 Problem Formulation

### 4.2.1 Description of Models

The objective of RPM is to make sure that active power imbalances arising from forecasting and other unplanned errors are balanced during real-time operation. Hence, deviations from the production and consumption plans from DAM need to be modeled to characterize the response of generators in the RPM. With new players in the electricity market from the demand-side such as EV aggregator [65], the planning stage before the DAM participation becomes ever more important if they are to partake in arbitrage. Consequently, it is necessary to mathematically model the EV aggregator planning model, and its subsequent participation in the day-ahead and regulating power market. The relationship between the markets are shown in Figure 4.1.

The following approach is used to characterize the relationship between the models:

- Use EV aggregator planning model to find the hourly aggregated charging schedule of EVs over the planning horizon.
- The hourly charging schedule of EVs is then taken as a fixed demand along with the conventional demand and used in the ACOPF model to obtain the actual generation dispatch while considering the major operating constraints. The ACOPF performed also gives the incremental transmission losses at every bus in the system.
- The incremental transmission loss (ITL) is used to calculate the loss penalty factor, which in turn is used to modify the up and down regulation incremental cost

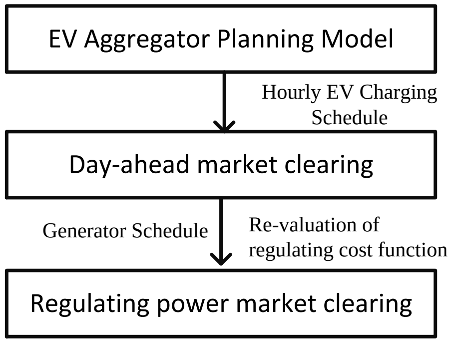


Figure 4.1: Relationship between the models

functions. Doing this will reflect the effect of increment or decrement of power at a bus on the total transmission loss in the system. The re-valued incremental cost functions are used in the RPM model to finally determine the necessary regulating power.

### 4.2.2 EV Aggregator Planning Model

The EV aggregator model characterizes the flexibility available from the batteries of EVs and schedules their charging energy. It is imperative to have good estimate of the electricity price profile for planning the scheduling of EV charging. Considering an electricity market with nodal pricing, the price of electricity depends on the generation technology mix, the demand profile and the topology of the transmission system. A DCOPF framework [66] is used to account for these factors in the aggregator planning model and a global analysis is assumed to be performed by the aggregator. Therefore, it is assumed that the aggregator has the information with regards to generator cost functions, conventional load profile and the transmission network parameters. Based on the estimated data, the EV aggregator simulates the scheduling of generators and simultaneously plans for EV charging energy in a way so as to minimize the total cost of power generation as shown in (4.1).

$$Minimize \quad DAEC = \sum_{i \in N} \sum_{t \in T} C_i(P_{i,t}) \tag{4.1}$$

The objective function of the EV aggregator formulated in (4.1) is subject to the constraints (4.2)-(4.5) by the EV batteries and also constraints (4.6)-(4.8) imposed by the power system.

#### 4.2.2.1 EV Related Constraints

The EV aggregator estimates the amount of energy that the EVs would need for travel during the battery charge scheduling horizon. Considering that the EV aggregator participates in RPM, it is necessary for the aggregator to forecast the regulating power volume and the regulating direction (i.e., up or down regulation) during the participating hour. If up regulation is provided using vehicle-to-grid (V2G) concept, the aggregator needs to plan for the additional energy charging needed for participating in the RPM.

Based on this charging requirement information and plan for participation in RPM, the batteries are charged only that amount of energy necessary over their initial state. Note that vehicles may travel more or less than the average distance considered. A minimum charge in the battery is always maintained to provide a possibility of backup energy in case the distance traveled needs to be higher than the average distance as shown in (4.2).

$$SOC_i^{ini} + \sum_{t=1}^{T} E_{i,t} = SOC_i^{min} + \sum_{t=1}^{T} (E_{i,t}^{next} + E_{i,t}^{up}); \qquad \forall i \in N_V \tag{4.2}$$

The EV aggregator needs to schedule the charging of the EVs in such a way that the battery is charged before travel during hour $t$. Additionally, the battery also needs to be charged with the extra energy needed for up regulation before the participating hour $t$. This constraint is formulated as shown in (4.3).

$$\sum_{h=1}^{t-1} E_{i,h} - E_{i,h}^{next} - E_{i,h}^{up} \geq E_{i,t}^{next} + E_{i,t}^{up}; \qquad \forall t \in T, i \in N_V \tag{4.3}$$

Charging and discharging of the battery during consecutive hours results in a change in its energy level. This is formulated as shown in (4.4).

$$SOC_{i,t} = \begin{cases} SOC_i^{ini} + E_{i,t} - E_{i,t}^{next} - E_{i,t}^{up} & \forall t \in \{1\}, i \in N_V \\ SOC_{i,t-1} + E_{i,t} - E_{i,t}^{next} - E_{i,t}^{up} & \forall t \in \{2, 3..., T\}, i \in N_V \end{cases} \tag{4.4}$$

The energy level in the battery should not deviate from its minimum and maximum limits as shown in (4.5).

$$SOC_i^{min} \leq SOC_{i,t} \leq SOC_i^{max}; \quad \forall t \in T \tag{4.5}$$

#### 4.2.2.2 Power System Constraints

It has to be ensured that the total power injected at a bus is equal to the total power withdrawn from the bus as shown in (4.6). The demand at bus $i \in N_V$ also includes the

EV demand that is scheduled and is one of the results from the optimization model.

$$P_{i,t} - PL_{i,t} - E_{i,t} - \sum_{j \in N} B_{i,j}\delta_{j,t} = 0; \quad \forall i \in N, t \in T \tag{4.6}$$

It is imperative that the generators observe the minimum and maximum values of their active power generation limits as shown in (4.7).

$$P_i^{min} \leq P_{i,t} \leq P_i^{max}; \quad \forall i \in N, t \in T \tag{4.7}$$

There is only a certain amount of power that can be transmitted over the transmission lines and these limits are satisfied by using (4.8).

$$B_{i,j}(\delta_{i,t} - \delta_{j,t}) \leq L_{i,j}^{max}; \qquad \forall i, j \in N_L \tag{4.8}$$

### 4.2.3 Day-Ahead Market Model

The day-ahead market is represented using an ACOPF in this chapter for the following reasons: a) to estimate the actual state of the power system before the regulation hour; b) to accurately characterize the associated transmission loss and its incremental deviation with respect to changes in the injected power at various buses during the regulating hour. For any regulating hour $t' \in T$, the results of actual generation scheduling and line flows can be obtained as described below.

Within the ACOPF framework, the day-ahead market model is cleared with the objective of minimizing the total cost of generation to supply the demand as shown in (4.9) subject to the system constraints shown in (4.10)-(4.17).

$$Minimize \quad DAC_t\Big|_{t=t'} = \sum_{i \in N} C_i(P_{i,t}\big|_{t=t'}) \tag{4.9}$$

It has to be ensured that both the active and reactive power balance at each bus is satisfied. The power injected into the bus should be equal to the power withdrawn from the bus at any time $t = t'$ as shown in (4.10) and (4.11) for active and reactive powers, respectively. For the ACOPF, the planned energy consumption $E_{i,t}$ from the EV aggregator model is provided as an input parameter for every time $t = t'$.

$$P_{i,t}\big|_{t=t'} - PL_{i,t}\big|_{t=t'} - E_{i,t}\big|_{t=t'} - P(V, \delta) = 0; \quad \forall i \in N \tag{4.10}$$

$$Q_i - QL_i - Q(V, \delta) = 0; \quad \forall i \in N \tag{4.11}$$

Each generator has a maximum amount of active and reactive power that it can produce for each time $t = t'$ as shown in (4.12) and (4.13), respectively.

$$P_i^{min} \leq P_{i,t}\big|_{t=t'} \leq P_i^{max}; \quad \forall i \in N \tag{4.12}$$

$$Q_i^{min} \leq Q_i \leq Q_i^{max}; \quad \forall i \in N \tag{4.13}$$

The voltage at every bus in the power system has to be within the specified limits as shown (4.14).

$$V_i^{min} \leq V_i \leq V_i^{max}; \quad \forall i \in N \tag{4.14}$$

It should also be ensured that the total power transmitted over the transmission lines do not exceed the maximum possible limit as shown in (4.15).

$$L_{i,j} \leq L_{i,j}^{max}; \quad \forall i, j \in N_L \tag{4.15}$$

There should be sufficient active power reserves available within the power system in order to ensure its secure operation during emergency imbalance conditions. This is obtained using (4.16) for up-regulating reserves and (4.17) for down-regulating reserves.

$$\sum_{i \in N_G} (P_i^{max} - P_{i,t}\big|_{t=t'}) \geq P^{R+} \tag{4.16}$$

$$\sum_{i \in N_G} (P_i^{min} - P_{i,t}\big|_{t=t'}) \leq P^{R-} \tag{4.17}$$

The results from this model also yield the associated transmission losses and the corresponding incremental transmission loss (ITL) [66] as shown in 4.18.

$$ITL_i(P_{i,t}\big|_{t=t'}) = \frac{\partial P_{loss}}{\partial P_i}; \tag{4.18}$$

The penalty factor at bus $i$ can be calculated from ITL as shown in (4.19).

$$PF_i = \frac{1}{1 - ITL_i(P_{i,t}\big|_{t=t'})} \tag{4.19}$$

The calculated penalty factor could then be used to re-value the marginal price of regulating power within the regulating power market model as shown in (4.25). The re-valuation reflects the effect of transmission loss from regulating power injection at bus $i$ on the associated changes in regulation costs due to the same .

### 4.2.4 Regulating Power Market Model

#### 4.2.4.1 Objective function of RPM

The objective function of the RPM is to minimize the total cost of power balancing [67]. It can be mathematically formulated as in (4.20).

$$\textit{Minimize:} \quad RP = \sum_{i=1}^{N_G}[c_i^+ \Delta P_i^+ - c_i^- \Delta P_i^-] + \sum_{i=1}^{N_V}[c_i^+ \Delta EV_i^+ - c_i^- \Delta EV_i^-] \quad (4.20)$$

The objective function of RPM model is subjected to constraints (4.21) - (4.27).

#### 4.2.4.2 Regulating power limits

There is a regulating range within which power can be up or down regulated by a production balance responsible party (BRP) at any node $i$ in the system and is shown in (4.21) and (4.22), respectively.

$$\Delta P_i^+ \leq (P_i^{max} - P_{i,t}\big|_{t=t'}); \quad \forall i \in N_G \quad (4.21)$$

$$\Delta P_i^- \geq (P_i^{min} - P_{i,t}\big|_{t=t'}); \quad \forall i \in N_G \quad (4.22)$$

Based on generator scheduling in the day-ahead market, the available regulating power can be obtained. It is assumed that all the regulating power available in the system during an operational hour is made available to the RPM.

Modeling of EV participation in the day-ahead market is done as described in Section 5.3.1. Additionally, the up and down regulating power available from the EVs after the day-ahead market clearing can be obtained as shown in (4.23) and (4.24), respectively.

$$\Delta EV_i^+ \leq min[E_{i,t}^{up}\big|_{t=t'}, DP_{i,t}\big|_{t=t'}]; \quad \forall i \in N_V \quad (4.23)$$

$$\Delta EV_i^- \geq max[(SOC_{i,t}\big|_{t=t'} - SOC_i^{max}), -CP_{i,t}\big|_{t=t'}]; \quad \forall i \in N_V \quad (4.24)$$

The up regulating power from EVs is a net aggregate of V2G discharge power from the battery during the regulating hour.

#### 4.2.4.3 Re-valued Price

The regulating power prices in the RPM are determined based on re-valued incremental cost function of the BRP to take into account the additional costs due to transmission losses within the network [68]. This is described in (4.25).

$$c_i^+, c_i^- = \frac{\partial C_i(P_{i,t})}{\partial P_{i,t}} PF(i); \qquad \forall t = t' \tag{4.25}$$

#### 4.2.4.4 Transmission Line Limits

The transmission line constraint is formulated as shown in (4.26). This indicates that the change in active power flow over the line should not exceed its maximum limit.

$$L_{i,j} + \sum_{k}^{N} ptdf_{i,j,k}(\Delta P_k^+ + \Delta P_k^- + \Delta EV_k^+ + \Delta EV_k^-) \leq L_{i,j}^{max}; \; \forall i,j \in N_L \tag{4.26}$$

#### 4.2.4.5 Active power balance

It should be noted that the net active power injection at any bus $i$ should be equal to zero. This is formulated as shown in (4.27)

$$\sum_{i}^{N} [\Delta P_i^+ + \Delta P_i^- + \Delta EV_i^+ + \Delta EV_i^-] - \sum_{i}^{N} P_i^{dev} = 0 \tag{4.27}$$

## 4.3 Case Study and Results

The proposed RPM model with EVs is applied to a case study using a modified Nordic 32-bus test system [69] shown in Figure 4.2. This test system is representative of the Swedish high voltage transmission network connecting the abundant hydro generators in the North to the load-centric South.

### 4.3.1 Data Setup

Quadratic cost functions were used for the generators present in the system and were obtained from [70]. Transmission line flow limits of 800MVA-1000MVA were assigned for these simulations where not explicitly provided in [69]. For DCOPF model, it was considered that the system must be N-1 contingency compliant and the MVA capacity was assumed to be limited to 80% of the value provided in the test system data. Additionally, it was also assumed that the system load was operating at an overall lagging power factor of 0.9 during normal operation. Hence, the active power transmission capacities were

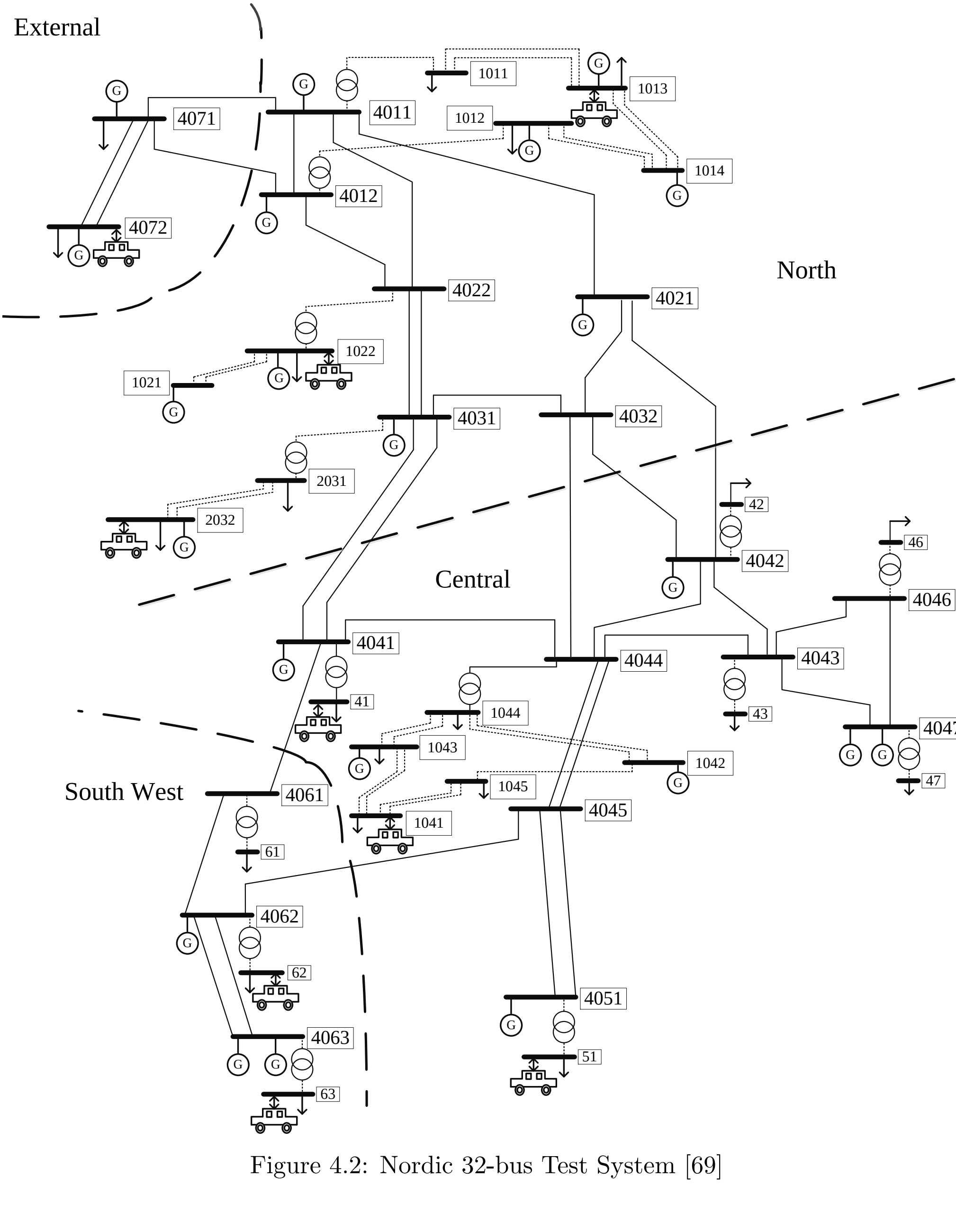


Figure 4.2: Nordic 32-bus Test System [69]

limited to $(0.9 * 0.8 \approx 0.7)$, i.e., 70% of the 800-1000 MVA values during the planning stage.

The load profile over the day was obtained from [71] for the third Monday in December, 2012 and normalized to be made usable for the test system. It was further assumed that the conventional demand at all the nodes experienced the same profile over the day.

Considering planning for day-ahead and regulating power markets, the planning horizon for the EV aggregator model is assumed to be 24 hours. The EV related parameters used in the case study were obtained from [72]. The value of $SOC_i^{min}$ was fixed at 20% of battery capacity to allow for a reserve in case the distance traveled needs to be higher than 40 km. Similarly, $SOC_i^{max}$ was fixed at 85% of battery capacity to account for the changes in aggregated battery capacity limits when a significant number of vehicles are unavailable to the aggregator while traveling. The EV demand was assumed to be present mostly at the load-centric buses. The following buses were assumed to share the aggregated EV demand: 4072, 1013, 1022, 2032, 1041, 41, 51, 62 and 63. The total number of vehicles present at these buses were assumed to be 50000 with 10% EV penetration. This is estimated to be the maximum amount of EV penetration in the Swedish automobile market by 2030 in the 'current control measure' scenario provided in [73].

The magnitude of total real time deviation for the case of up regulating power was assumed to be 159 MW and for the case of down regulating power, it was taken to be 147.9 MW. These values are approximately half of the reserve requirement in the Nordic system of around 1620 MW [74] when scaled down to be consistent with the Nordic 32-bus test system.

## 4.3.2 Results

### 4.3.2.1 Scheduling by EV aggregator

The EV aggregator planning model schedules the charging of EVs in such a way that they charge during the low electricity price hours. Since, it is assumed that all the EVs not driving during a particular hour are available for charging, the EVs are scheduled for charging by the aggregator in all the scenarios considered occurs between hours $t1 - t6$ of the day. Hence, the EVs are charged even the energy necessary for up regulation through V2G and available for activation during the rest of the hours between $t7 - t24$.

### 4.3.2.2 Day-ahead market clearing

The generation dispatch and corresponding locational marginal price (LMP) results from the ACOPF are shown in Table 4.1. It can be seen that most of the generators are running at their maximum capacity. Furthermore, the difference in LMPs of the buses in the North and South regions of the test system are significant due to difference in marginal production cost and additional congestion in the network. It can be seen that the LMP at load buses is significantly high making it difficult for EVs to compete in the RPM, especially for up regulating power. But, with the EV aggregator model, the EVs can charge $E_{i,t}^{up}$ during low price periods and re-sell it for up regulation during high price periods with a margin. A similar approach would apply for down regulation by EVs.

Table 4.1: Result from day-ahead market model: Hour 18

| Bus [$No.$] | Power Generation [$MW$] | LMP [€/$MWh$] |
|---|---:|---:|
| 4072 (EV) | 1561.4 | 23.5 |
| 4071 | 500.0 | 23.3 |
| 4011 | 1000.0 | 23.8 |
| 4012 | 800.0 | 22.6 |
| 4021 | 300.0 | 60.9 |
| 4031 | 350.0 | 67.9 |
| 4042 | 700.0 | 73.2 |
| 4062 | 207.0 | 84.5 |
| 4063 | 219.9 | 85.3 |
| 4051 | 700.0 | 77.6 |
| 4047 | 1200.0 | 74.1 |
| 2032 (EV) | 850.0 | 62.9 |
| 1013 (EV) | 268.8 | 21.9 |
| 1012 | 528.9 | 18.2 |
| 1014 | 700.0 | 21.3 |
| 1022 | 0.0 | 22.8 |
| 1021 | 207.7 | 21.6 |
| 1043 | 200.0 | 77.8 |
| 1042 | 400.0 | 73.7 |
| 1041 (EV) | 0.0 | 80.2 |
| 41 (EV) | 0.0 | 74.2 |
| 62 (EV) | 0.0 | 84.5 |
| 63 (EV) | 0.0 | 85.3 |
| 51 (EV) | 0.0 | 77.5 |

#### 4.3.2.3 Regulating power activation

Considering the existing operation of RPM in the Nordic region, manual reserves are activated based on the merit order. This is subject to the condition that there is no congestion caused due to the activation of these reserves. The results, when applied to the test system considered, are compared with the results obtained using the RPM model proposed in this chapter, with and without EV participation. This is done for two scenarios- one where the TSO requests up regulating power and two, where the TSO requests down regulating power.

Table 4.2: Result: Up regulating power hour 18

| Bus [$No.$] | Merit Order [$MW$] | RPM, without EV [$MW$] | RPM, with EV [$MW$] |
|---|---|---|---|
| 4062 | 29.8 | 32.6 | 21.9 |
| 4063 | 23.4 | 19.5 | 9.2 |
| 1012 | 105.8 | 105.9 | 106.8 |
| 2032 (EV) | - | - | 5 |
| 1041 (EV) | - | - | 5 |
| 41 (EV) | - | - | 5 |
| 51 (EV) | - | - | 5 |
| $\Delta P$ | 159.0 MW | 158.0 MW | 157.9 MW |
| $\Delta P_{loss}$ | 11.1 MW | 10.1 MW | 10.0 MW |

Table 4.3: Result: Up regulating power prices at hour 18

| Bus [$No.$] | Merit Order [€$/MWh$] | RPM, without EV [€$/MWh$] | RPM, with EV [€$/MWh$] |
|---|---|---|---|
| 4062 | 86.267 | 86.432 | 85.797 |
| 4063 | 86.649 | 86.421 | 85.806 |
| 1012 | 18.700 | 18.701 | 18.706 |
| 2032 (EV) | - | - | 67.970 |
| 1041 (EV) | - | - | 85.192 |
| 41 (EV) | - | - | 79.204 |
| 51 (EV) | - | - | 82.547 |

Table 4.4: Result: Total up regulation cost at hour 18

| Merit Order[€] | RPM, without EV [€] | RPM, with EV [€] |
|---|---|---|
| 6576.80 | 6483.33 | 6240.74 |

In the first scenario, the TSO request up regulating power from the generators and EV aggregator for the hour 18. The total active power deviation in the system that results in the request for up regulting power is assumed to be 159 MW. The resulting comparison of up regulating power activation is shown in Table 4.2. The comparison is done for three cases- activation using merit order, RPM model without regulating power from EV and RPM model with regulating power from EV. The corresponding up regulation prices and regulation costs incurred by the TSO are shown in Tables 4.3 and 4.4, respectively. It can be seen that the total regulation costs incurred by the TSO decreases when the effect of transmission losses are considered with the inclusion of the loss penalty factor. The EVs present near the load centre are particularly effective in reducing the costs by injecting power close to the load centres.

Table 4.5: Result: Down regulating power at hour 18

| Bus<br>[$No.$] | Merit Order<br>[$MW$] | RPM, without EV<br>[$MW$] | RPM, with EV<br>[$MW$] |
|---|---|---|---|
| 1012 | -105.80 | -105.80 | -105.80 |
| 1014 | -31.80 | -31.80 | -12.70 |
| 4072 (EV) | - | - | -6.40 |
| 1013 (EV) | - | - | -6.40 |
| 1022 (EV) | - | - | -6.40 |
| $\Delta P$ | -137.60 MW | -137.60 MW | -137.70 MW |
| $\Delta P_{loss}$ | -10.30 MW | -10.30 MW | -10.20 MW |

Table 4.6: Result: Down regulating power prices at hour 18

| Bus<br>[$No.$] | Merit Order<br>[€/$MWh$] | RPM, without EV<br>[€/$MWh$] | RPM, with EV<br>[€/$MWh$] |
|---|---|---|---|
| 1012 | 17.60 | 17.60 | 17.600 |
| 1014 | 21.33 | 21.33 | 21.264 |
| 4072 (EV) | - | - | 18.519 |
| 1013 (EV) | - | - | 16.898 |
| 1022 (EV) | - | - | 17.757 |

Table 4.7: Result: Total down regulation cost at hour 18

| Merit Order[€] | RPM, without EV [€] | RPM, with EV [€] |
|---|---|---|
| -6142.61 | -6141.08 | -6211.78 |

In the second scenario, the total active power deviation in the system is assumed to result in down regulating power request by the TSO. The magnitude of power deviations is considered to be 147.9 MW. Similar to the previous scenario, three cases of down regulating power activation are compared- activation from merit order, RPM model without down regulating power from EV and RPM model with down regulating power from EV. The down regulating power activation results are compared in Table 4.5 and the corresponding down regulation prices and regulation costs for the TSO are shown in Tables 4.6 and 4.7, respectively. In the case of down regulating power activation, there is only a small difference in the cost between the merit order activation method and the proposed RPM model with EVs. This could be seen as advantageous from both the system perspective, where EV participation in down regulation does not significantly increase the cost of balancing, as well as from EV perspective as their batteries could be charged at a price generally lower than the day-ahead price.

## 4.4 Summary

A regulating power market model considering the participation of EV aggregator was developed. The model was used to activate regulating power by re-valuating the marginal cost of regulating power using a penalty factor calculated from ACOPF to account for their influence on active power losses on the transmission lines. A case study was performed on a modified Nordic 32-bus system considering two regulating power activation scenarios. Within the scope of this study it could be seen that the system could benefit from the aggregated regulating power provided by EVs. Considering the effect of regulating power on transmission line losses also results in slightly different set of regulating power activation when compared to the merit order list while also resulting in lower total balancing costs. This is clearly noticeable in the case study when up regulating power scenarios are considered. It should, however, be mentioned that the activation of EVs for active power regulation would be very much dependent on their position to perform arbitrage and a more detailed analysis regarding this needs to be done.

# Chapter 5

# Electricity Retailer Planning Considering EV Energy Scheduling

*This chapter proposes an energy portfolio optimization model for an EV aggregator or electricity retailer incorporating the market functions of an EV aggregator. The retailer could use this model for making decisions regarding purchase of power contracts from forward markets as well as for setting prices for customers entering into fixed and variable retail contracts. The proposed retailer planning (RP) model is used in a case study involving a typical retailer in Sweden assuming the role of an EV aggregator in the market. Results from the case study indicate that variable retail contracts could prove to be beneficial to both the vehicle owners and the retailer in the presence of complete EV energy scheduling flexibility.*

## 5.1 EV aggregator and Electricity Retailer

An electricity retailer performs the task of a ”middleman” between the wholesale electricity market and small/medium end-users. The retailer faces two major issues during the planning stage. Firstly, the cost of purchasing electricity will depend on its price in the spot market at a future point in time and the corresponding demand of its customers, both of which are uncertain. Secondly, the retailer has to determine competitive retail prices for its customers. To alleviate the risks associated with uncertain prices, the retailer can procure part of the end-user demand through forward power contracts, where the price for electricity is fixed over the contract period [22]. Recently, various models have been proposed for forward contract portfolio optimization of an electricity retailer while accounting for the stochastic behavior of electricity price and demand [75], [76]. In [75], a stochastic model was developed with a cost minimization objective to manage the forward contracting decision accounting for the involved risk. In [76], the proposed stochastic model maximizes the profits of the retailer while determining forward contracts to be signed and the selling prices for its customers.

Emerging technologies such as EVs provide an added possibility of short-term response from the demand side. The opportunities for exploiting EVs as flexible demand have been discussed in [4], [77]. In [78], the elasticity of electric vehicle demand is considered and a short-term model is proposed that optimizes the portfolio of an EV aggregator through its participation in the day-ahead and secondary reserves markets. An electricity retailer has a good possibility of transitioning into the role of an EV aggregator. In such an environment, it becomes imperative for the retailer to accommodate the needs and short-term flexibility of EVs while managing its portfolio over a longer time frame.

In this chapter, a stochastic programming approach (see e.g., [79], [80]) is proposed that manages the portfolio of an electricity retailer who additionally assumes the role of an EV aggregator. The model presented in [76] was adopted and further developed by considering a price-taking retailer that optimizes its portfolio over a medium-term horizon with hourly discretization while scheduling the EV demand. The retailer considers the possibility to enter into power contracts in the forward electricity market and offers fixed and variable price contracts to its customers. In a fixed retail contract, it is assumed that the retailer determines and sells electricity at a constant price per MWh whereas, in a variable retail contract, the customer is charged based on the volume weighted average of the electricity price at the spot market. The objective of the retailer is to maximize its expected profits while considering the risks associated with spot price and demand uncertainties.

In the proposed approach, a retailer would perform the following functions: i) optimize the EV charging demand using expected spot price signals, ii) determine its yearly, quarterly and monthly forward contracts to be entered into, iii) determine the selling price for its existing customers with fixed and variable retail contracts. With this arrangement, the benefit for flexibility offered by EV customers would be the possibility to charge their vehicles during periods of low electricity price. The retailer is considered to aid the customers by suggesting a charging profile based on their charging requirements one day in advance. By following the charging profile provided by the retailer, EV customers would pay a discounted retail price for vehicle charging and help the retailer adhere to its plan thereby reducing the imbalance costs.

## 5.2 Electricity Market Framework

### 5.2.1 Market Structure

The proposed price-taker retailer planning model is set in the context of the Nordic electricity market, Nordpool [41]. The retailer is considered to purchase power from two main power markets namely, the spot and the forward markets and resell power to end-users through retail contracts. The forward contract to be entered into by the retailer can be yearly, quarterly or monthly base load contracts [22]. The retailer is assumed to offer two types of retail contracts to its customers namely, fixed and variable price contracts. The total user demand of the retailer is assumed to consist of an inflexible conventional demand and a flexible EV demand. The total demand of the customers is assumed to be satisfied by the retailer through the purchase of power from either the spot and/or the forward markets. Figure 5.1 describes the main elements in the proposed planning framework.

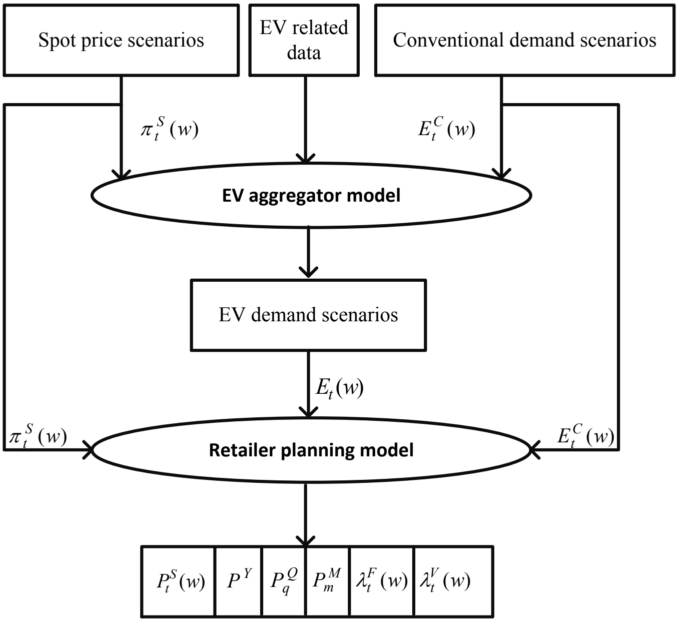


Figure 5.1: Electricity market framework for the retailer

In a forward power contract, a buyer and a seller enter into a financial agreement on the lock-in price for a certain quantity of electric power over a pre-determined future time period. Therefore, the power contracted in the forward market and the corresponding price remains constant over the delivery period. The delivery period indicates the time period over which the forward contract is put into effect. Based on the type, forward contracts can be classified as base load and peak load contracts. In the Nordpool forward market, base load contracts are traded round the clock while peak load contracts are traded for the 08:00-20:00 time horizon. Additionally, base load and peak load contracts are traded as yearly, quarterly and monthly contracts depending on the time period of maturity [22]. Only base load yearly, quarterly and monthly contracts are considered in the retailer planning model described in this chapter although peak load contracts can be similarly incorporated. The base forward prices in this chapter are calculated as described in Section 5.3.2.

The EV aggregator demand scheduling model developed [72] reflects the charging and discharging operation of an aggregated battery in accordance with the needs of all the catered EV owner, while respecting the restrictions imposed by driving needs and the battery's energy limits. The discharging of the batteries is considered to occur only when the EVs are driving. The model takes the estimated spot price, conventional demand and EV related data as input and outputs the optimal charging schedule for the EVs based on a least charging cost objective. The charging schedule from the EV aggregator model is then provided as an input to the retailer planning (RP) model along with the estimated conventional demand and spot price. The optimized results from the RP model outputs the power contracts to be entered into by the retailer in the forward market while also determining the retail prices to be set by it.

## 5.3 Retailer Planning Model

It is assumed that the EV demand is responsive to the spot price and is scheduled by the EV aggregator model which has an objective of minimizing the total electricity charging cost. For each scenario of spot price and conventional demand, the aggregator model provides an EV demand scenario. The EV demand scenarios are then provided to the retailer planning model as parameters along with spot price and conventional demand scenarios. A scenario tree representing the decisions made is shown in Figure 5.2. The forward prices can be estimated at the time when purchase plans are to be made in the forward market and are called *here-and-now* decisions. The conventional demand and EV demand traded in spot market is a *wait-and-see* decision since it is highly uncertain until the clearing of the spot market and the announcement of spot prices.

### 5.3.1 EV Aggregator Model

The EV aggregator model can be used by the electricity retailer to utilize the short-term elasticity offered by the EVs owned by its customers. As described in Figure 5.1, the model inputs are the estimated spot price and conventional demand along with the EV related data. The output from the model is a least cost schedule for EV battery charging. Note that this approach inherently considers the correlation between spot price and conventional demand while scheduling the aggregated EV demand.

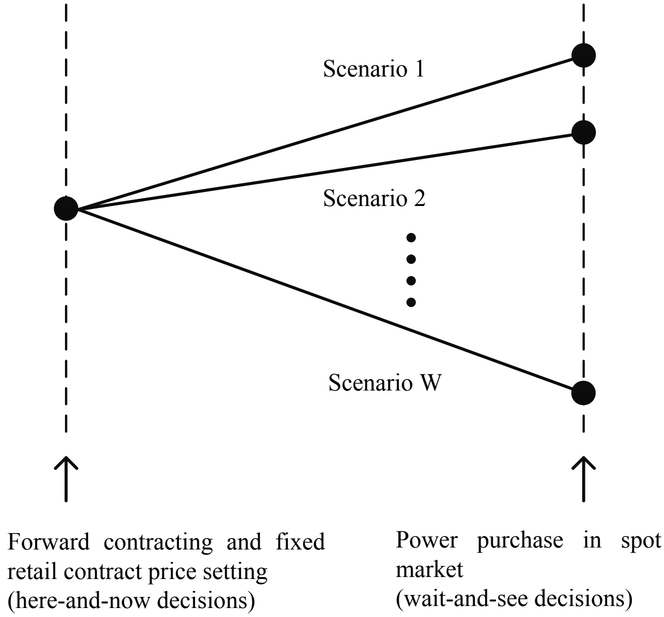


Figure 5.2: Scenario tree used in the RP model [76]

The optimization horizon for the EV aggregator model is considered to be $H$ hours and is performed repeatedly to cover the planning horizon of $T$ hours and scenarios subsequently generated in the RP model. The EV aggregator model is mathematically formulated as described below.

#### 5.3.1.1 Objective Function of EV Aggregator

The objective function of the EV aggregator model is to minimize the total charging cost over the scheduling time horizon. This can be formulated as,

$$Minimize\ ACC = \sum_{h \in H} \pi_h^S E_h \tag{5.1}$$

This objective of the EV aggregator is subject to the constraints presented in (5.2)-(5.5). The charging schedule obtained from this model is then utilized by the retailer to estimate its total end user demand as will be described in Section 5.3.4. It should be noted from (5.1) that all EV owners are assumed to enter into a variable price retail contract. Through this scheduling, the EV owners would pay for the amount of energy they consume during periods of relatively low prices in the spot market.

#### 5.3.1.2 Minimum Energy Requirement

The retailer estimates the amount of energy that the EVs would need for travel during the battery charge scheduling horizon. Based on this, the batteries are charged only that amount of energy necessary over their initial state. Note that vehicles may travel more or less than the average distance considered. $SOC^{min}$ is utilized to provide a possibility of reserve energy in case the distance traveled needs to be higher than the average distance as shown in (5.2).

$$SOC^{ini} + \sum_{h=1}^{H} E_h = SOC^{min} + \sum_{h=1}^{H} E_h^{next} \tag{5.2}$$

#### 5.3.1.3 The Charging Period Limit

The retailer needs to schedule the charging of the EVs in such a way that the battery is charged before the travel during hour $h$ as shown in (5.3).

$$\sum_{hf=1}^{h-1} E_{hf} - E_{hf}^{next} \geq E_h^{next}; \quad \forall h \in H \tag{5.3}$$

#### 5.3.1.4 The Battery State

Charging and discharging of the battery during consecutive hours results in a change in its energy level. This is formulated as shown in (5.4).

$$SOC_h = \begin{cases} SOC^{ini} + E_h - E_h^{next} & \forall h \in \{1\} \\ SOC_{h-1} + E_h - E_h^{next} & \forall h \in \{2, 3..., H\} \end{cases} \tag{5.4}$$

#### 5.3.1.5 Battery Energy Limits

The energy level in the battery should remain within its minimum and maximum limits as shown in (5.5).

$$SOC^{min} \leq SOC_h \leq SOC^{max}; \quad \forall h \in H \tag{5.5}$$

### 5.3.2 Forward Contract Cost

The costs associated with contracting power from the forward market by an electricity retailer consists of yearly, quarterly and monthly contracts. The total cost incurred by the retailer from forward contracts over a time period can be formulated as in (5.6).

$$C_t^F = (\pi_t^{FY} P_t^{FY}) + (\pi_t^{FQ} P_t^{FQ}) + (\pi_t^{FM} P_t^{FM}); \quad \forall t \in T \tag{5.6}$$

The contract price in the forward market is modeled as a simple linear function of the amount contracted to consider the fact that there is limited forward contracts accessible to the retailer. This is shown in (5.7)-(5.9). The base price for each of the forward contracts $\pi^{Ybase}$, $\pi^{Qbase}$, $\pi^{Mbase}$ is calculated using the estimated average spot price over the delivery period of the contract. The forward price function is assumed to be linear to make the problem simple and limit the order of the objective function to be quadratic in nature.

$$\pi_t^{FY} = \pi_t^{Ybase} + \rho^Y P_t^{FY}; \quad \forall t \in T \tag{5.7}$$

$$\pi_t^{FQ} = \pi_t^{Qbase} + \rho^Q P_t^{FQ}; \quad \forall t \in T \tag{5.8}$$

$$\pi_t^{FM} = \pi_t^{Mbase} + \rho^M P_t^{FM}; \quad \forall t \in T \tag{5.9}$$

The constraints (5.10)-(5.12) maintain the value of power purchased from each of the forward contracts over their delivery periods.

$$P_t^{FY} = PY_y v_{yt}; \quad \forall t \in T, y \in Y \tag{5.10}$$

$$P_t^{FQ} = PQ_q v_{qt}; \quad \forall t \in T, q \in Q \tag{5.11}$$

$$P_t^{FM} = PM_m v_{mt}; \quad \forall t \in T, m \in M \tag{5.12}$$

The constraint formulated in (5.13) denotes the non-negative nature of the power purchased.

$$P_t^{FY}, PY_y, P_t^{FQ}, PQ_q, P_t^{FM}, PM_m \geq 0; \quad \forall t \in T, y \in Y, q \in Q, m \in M \tag{5.13}$$

Decisions made in the forward market include the amount of power to be purchased from each of the base load contracts considering the scenarios associated with the uncertainty in spot prices and customer demand.

### 5.3.3 Cost of Purchase from Spot Market

In this proposed model, a part or all of the end user demand may be purchased by the retailer from the spot market. The prices in the spot market are uncertain in nature at the time when forward contract decisions are made and are modeled to be stochastic. The equation (5.14) denotes the cost arising from the purchase of energy from the spot market. The constraint (5.15) denoted the non-negative nature of the purchased power.

$$C_t^S(w) = \pi_t^S(w) P_t^S(w); \quad \forall w \in W \tag{5.14}$$

$$P_t^S(w) \geq 0; \quad \forall w \in W \tag{5.15}$$

### 5.3.4 The Power Balance

It is imperative that there is a balance between the energy bought and sold by the retailer. For every time period, the power balance is given as shown in (5.16):

$$P_t^D(w) = P_t^S(w) + P_t^{FY} + P_t^{FQ} + P_t^{FM}; \quad \forall w \in W \tag{5.16}$$

The retailer supplies the total demand through purchase of power from the spot and forward markets. From the expression (5.16), the total demand of the end users is the sum of conventional and EV demands as shown in (5.17):

$$P_t^D(w) = E_t(w) + E_t^C(w); \quad \forall w \in W \tag{5.17}$$

### 5.3.5 Revenue of the Retailer

The retailer obtains its revenue by selling electrical energy to end-users through fixed price and variable price contracts as shown in (5.18) and (5.20), respectively. Based on the retailer's estimated cost for a particular level of consumption, the customers are informed of the price for electricity over the lock-in period before they enter into a contract with the retailer. The determination of this price by the retailer can be formulated as,

$$R_t^F(w) = \lambda_t^F(w) P_t^D(w) \nu^F; \quad \forall w \in W \tag{5.18}$$

$$\lambda_t^F(w) = \pi_t^{FY} + \theta^F [\nu^F P_t^D(w) - P^{maxF}]; \quad \forall w \in W \tag{5.19}$$

From (5.18), the retail price for customers with fixed price contract is modeled to be dependent on the end-user demand as shown in (5.19). It is further considered that the retailer provides a "discount" on the pricing to its customers depending on their consumption level. Thus, the higher the consumption of customers, greater is the "discount" offered by the retailer.

In variable price contracts, the retailer charges the customers for their consumption over a period of time, e.g., one month. The pricing for variable price contracts are based on the spot price for electricity volume-weighed over a specified period of time, plus a markup [81] considering other costs incurred by the retailer such as imbalance cost. The determination of this price by the retailer is formulated as,

$$R_t^V(w) = \lambda_t^V(w) P_t^D(w) \nu^V; \quad \forall w \in W \tag{5.20}$$

$$\lambda_t^V(w) = \pi_t^S(w) + \theta^V[\nu^V P_t^D(w) - P^{maxV}]; \quad \forall w \in W \tag{5.21}$$

From (5.20), the retail price for customers with variable price contract is modeled to be dependent on the end-user demand as shown in (5.21). Similar to the case of a fixed price contract, it is further considered that the retailer provides a discount on the pricing to its variable price contract customers depending on their consumption level. Additionally, the discount provided by the retailer to variable price contract customers is assumed to be higher when compared to fixed price contract customers. This stems from the idea that the retailer assumes a higher risk from fixed price contracts as opposed to variable price contracts.

### 5.3.6 The Retailer's Expected Profit

The expected profit of the retailer is equal to the difference between the revenue expected to be obtained from selling electricity to end-users and the cost of purchasing this electricity from the spot and forward markets. This can be expressed as a risk neutral problem as shown in (5.22).

$$Exp[z] = \sum_{w \in W} prob(w) \sum_{t \in T} [R_t^F(w) + R_t^V(w) - C_t^S(w) - C_t^F] \tag{5.22}$$

Expression (5.22) clearly expresses the problem faced by an electricity retailer. It can be seen that the revenue of the retailer from selling electricity and the cost of buying electricity from the spot market are uncertain and scenario dependent. To alleviate this level of uncertainty, the retailer can purchase part of the electricity from the forward market where the prices are relatively more stable [82].

### 5.3.7 The Risk Management Constraint

There are numerous methods for measuring risk that have been proposed in literature and have been compared in [83]. The method used in this chapter is $CVaR$ [76], [84]. $CVaR$ for a profit function at a certain confidence level $\alpha \in (0, 1)$ is the expected value of profit based on the condition that the profit is less than or equal to $VaR$. $VaR$ is the highest possible profit value with a probability of $(1-\alpha)$. The advantage of $CVaR$ is that it also accounts for the low profit scenarios that occur past the $VaR$ risk threshold that is selected. For a profit function $z$, $CVaR$ can be obtained as,

$$prob(z \leq VaR_{\alpha}) = 1 - \alpha \tag{5.23}$$

$$CVaR_{\alpha} = Exp[z|z \leq VaR_{\alpha}] \tag{5.24}$$

For the profit function of the retailer, $CVaR$ calculation at a confidence level $\alpha$ can be translated into solving the following optimization problem [76],

$$Maximize_{\xi,\eta(w)} \ CVO = \left(\xi - \frac{1}{1-\alpha} \sum_{w \in W} prob(w) \quad \eta(w)\right) \tag{5.25}$$

Subject to,

$$\xi - \left(\sum_{t \in T} R_t^F(w) + R_t^V(w) - C_t^S(w) - C_t^F\right) \leq \eta(w); \quad \forall w \in W \tag{5.26}$$

$$\eta(w) \geq 0; \quad \forall w \in W \tag{5.27}$$

### 5.3.8 Objective Function of Retailer Planning Model

The objective function of the retailer considering the $\alpha - CVaR$ risk measure can now be formulated as,

$$\begin{aligned} Maximize \ \ RPO = \beta \Bigg( \sum_{w \in W} prob(w) \Bigg( \sum_{t \in T} R_t^F(w) + R_t^V(w) - C_t^S(w) - C_t^F \Bigg)\Bigg) \\ + (1-\beta) CVO \end{aligned} \tag{5.28}$$

The objective function in (5.28) is subject to the core problem constraints (5.6) through (5.21) and the constraints imposed by the risk measure (5.26)-(5.27). The RP model described above is a non-linear optimization problem to be solved by the retailer. Optionally, a risk weight factor is introduced to give the electricity retailer consideration over the extreme risks associated with the planning problem. The risk weight factor $0 \leq \beta \leq 1$ allows the retailer to follow a risk neutral plan when $\beta = 1$ or a risk-averse plan when $\beta = 0$.

## 5.4 Case Study

### 5.4.1 Description of the Case Study

A case study was performed to illustrate the proposed model using the data from a typical electricity retailer in Sweden. The case study considers that the retailer participates in the Nordpool forward and spot markets.

Three main sets of input data were used in this case study:

1. Spot market prices from NordpoolSpot
2. Electricity demand of the retailer's customers from a specific bidding area
3. Estimated EV demand based on customer statistics and data available for conventional vehicles in the area covered by the retailer.

The system spot price data was obtained from NordpoolSpot [85] for a period of one year available with an hourly resolution and used as the expected value in the model as shown in Figure 5.3. The base prices for yearly, quarterly and monthly forward contracts were subsequently estimated using the average spot price over the maturity periods.

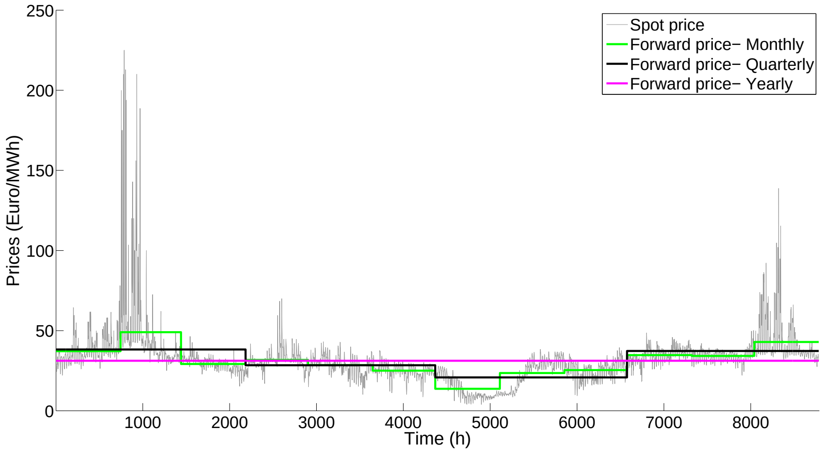


Figure 5.3: Spot market price and corresponding estimated base forward contract prices

The uncertainty associated with spot market prices was then modeled using a set of scenarios that were generated by adding a random term to the expected spot prices as shown in (5.29). Note that advanced techniques for forecasting model building and scenario generation could be easily used and integrated with the proposed approach.

$$\pi_t^S(w) = Exp[\pi_t^S] + G(\mu, \sigma); \quad \forall w \in W \tag{5.29}$$

The hourly conventional electricity demand of customers of a typical retailer in Sweden was obtained for a period of one year. The conventional demand data obtained corresponds to the same time period as that of the spot prices and was used as the expected demand. This is shown in Figure 5.4. The uncertainty associated with conventional demand was modeled in a manner similar to that of spot prices. A set of scenarios were generated by adding a random term to the expected conventional demand as shown in (5.30).

$$P_t^C(w) = Exp[P_t^C] + G(\mu, \sigma); \quad \forall w \in W \tag{5.30}$$

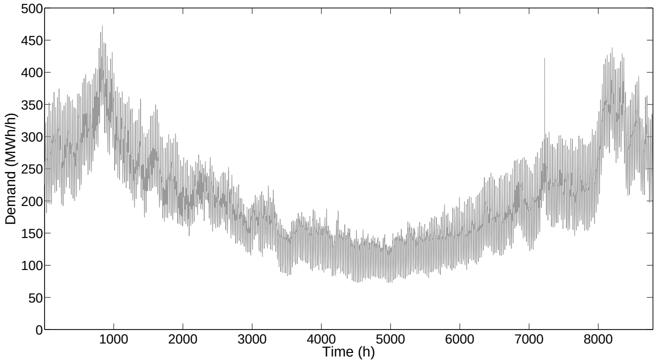

Figure 5.4: Estimated conventional demand of retailer's customers

Some of the EV related data has been derived from existing data on conventional fossil fueled vehicles. The total number of existing household cars has been obtained using statistical data available in [86] for the city of Gothenburg. The penetration level of EVs is then defined as the ratio of number of EVs to the total number of vehicles in the system, expressed in percentage.

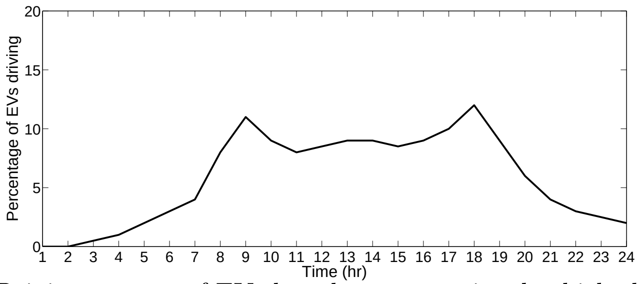

Figure 5.5: Driving pattern of EVs based on conventional vehicle data [48], [72]

The driving pattern of EVs is further derived based on conventional vehicle user pattern as shown in Figure 5.5. It is based on the assumption that human behavior will be independent of the type of vehicle driven. It is also assumed that the driving pattern is the same for all the days in the optimization horizon and the batteries of EVs not driving during any hour are available to the aggregator for scheduling. A 230 V single phase ac supply with a 16 A fuse that provides a maximum connection power of 3.68 kW is considered. This is the most widespread type of supply infrastructure available to the customers in Sweden [73]. The main EV parameter inputs to the EV aggregator model are shown in Table 5.1.

Table 5.1: EV Aggregator Model Input Parameters [48], [72]

| | |
|---|---|
| Battery Capacity | 24 kWh |
| Energy Consumption | 0.192 kWh/km |
| Distance Travelled | 40 km/day |
| Energy Consumption per Day | 7.68 kWh/day |
| Charging Power | 3.68 kWh/h |

The value of $SOC^{min}$ was fixed at 20% of battery capacity to allow for a reserve in case the distance traveled needs to be higher than 40 km. Similarly, $SOC^{max}$ was fixed at 85% of battery capacity to account for the changes in aggregated battery capacity limits when a significant number of vehicles are unavailable to the aggregator while traveling.

The parameter values used in the case study are shown in Table 5.2.

Table 5.2: Parameter values used in the case study

| | | | |
|---|---|---|---|
| $\alpha$ | 0.95 | $\theta^F$ | 0.0004 [€/MW$^2$h] |
| $\rho^Y$ | 0.3 [€/MW$^2$h] | $\theta^V$ | 0.0002 [€/MW$^2$h] |
| $\rho^Q$ | 0.32 [€/MW$^2$h] | $P^{maxF}$ | 500 MW |
| $\rho^M$ | 0.34 [€/MW$^2$h] | $P^{maxV}$ | 500 MW |

The RP model described in Section 5.3 was implemented in General Algebraic Modeling System (GAMS) using MINOS solver [87] that resulted in 298633 constraints, 298651 real variables 1150605 non-zero elements for a case with 10 scenarios.

### 5.4.2 Results and Discussions

#### 5.4.2.1 Scheduled EV demand

Various levels of EV penetration in the end-user market have been considered in this chapter and are based on studies conducted by [73], where an introduction of 600000 EVs has been estimated. This would result in approximately 13% EV penetration in Sweden. It is reasonable to consider that the penetration level of EVs might differ between regions and might be higher in cities and lower in smaller towns. Hence, an EV penetration level of 10-30 % has been considered in the case study. The resulting EV demand for an EV penetration level of 10%, over a period of one week for ten scenarios of the spot market price and conventional demand, is shown in Figure 5.6.

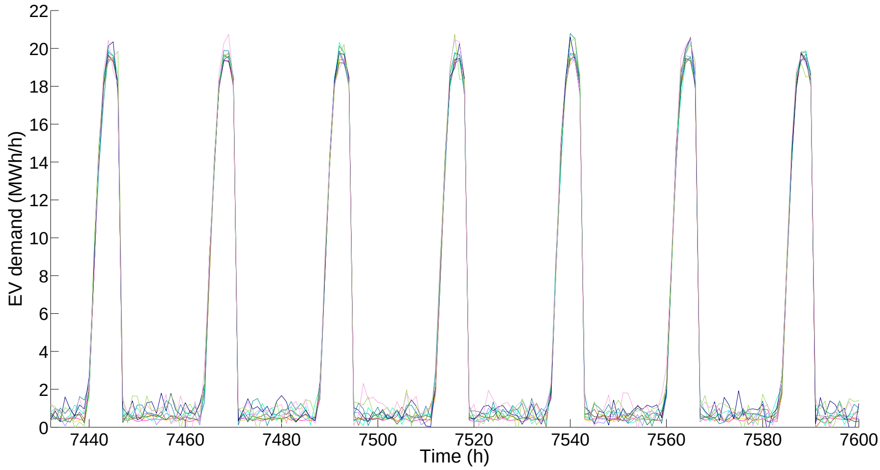


Figure 5.6: Demand scenarios generated by EV aggregator over one week for 10% EV penetration

#### 5.4.2.2 Forward contract decision by retailer

Figure 5.7 depicts the forward contract decisions made by the retailer when it is risk neutral ($\beta = 1$) and risk averse ($\beta = 0.1$). It can be observed that a risk averse retailer would purchase more power from the forward markets when the spot market prices are high.

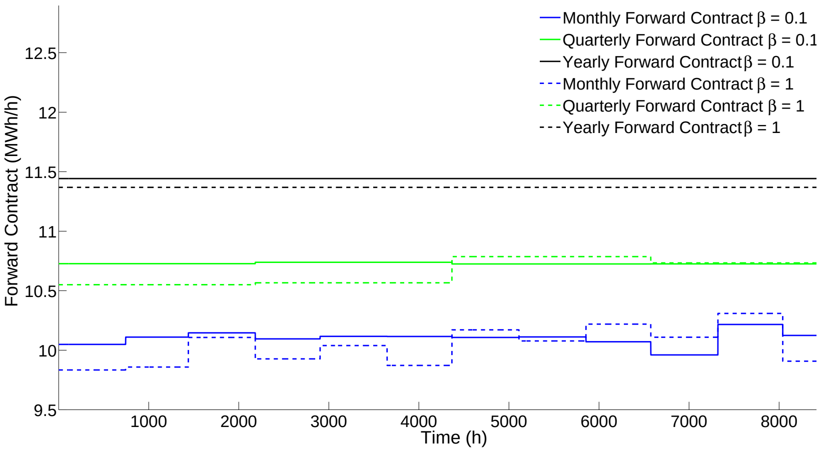


Figure 5.7: Forward contract decisions by the retailer when risk neutral and risk averse

#### 5.4.2.3 Retailer's profit

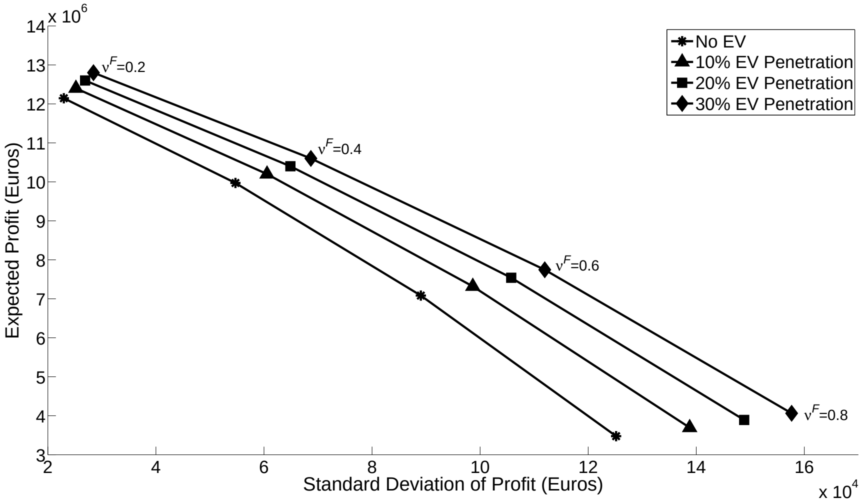


Figure 5.8: Expected profit versus standard deviation

Figure 5.8 shows the expected profit versus the standard deviation of profit for various levels of fixed price contract chosen by the end users. It can be noted that for the same total demand served, the expected profit of the retailer would increase if the fraction of end-user demand contracting fixed price contracts decreases. The opposite holds true for the corresponding standard deviation. With the increasing penetration of EVs, the standard deviation increases. The spread of standard deviation becomes larger as more customers of the retailer sign up for fixed price contracts at increasing EV penetration levels. This can be anticipated because with fixed price contracts, the retailer completely shields its customers from the price variations in the spot market, thereby incurring additional financial risks.

#### 5.4.2.4 Retail contract prices

Figure 5.9 shows the retail price offered by the retailer with increasing ratio of its customers opting for variable price contracts at 10% EV penetration. It can be seen that with increasing ratio of the retailer's customers opting for variable price contracts, the retail price offered by the retailer on fixed price contract increases. This can be accounted for by observing that the discount offered by the retailer on fixed retail contracts is volume weighed over the total contracted power by the fixed retail contract customers as shown in (5.19). In the case of variable price contracts, the retail prices offered are volume weighed based on the individual customer's demand profile.

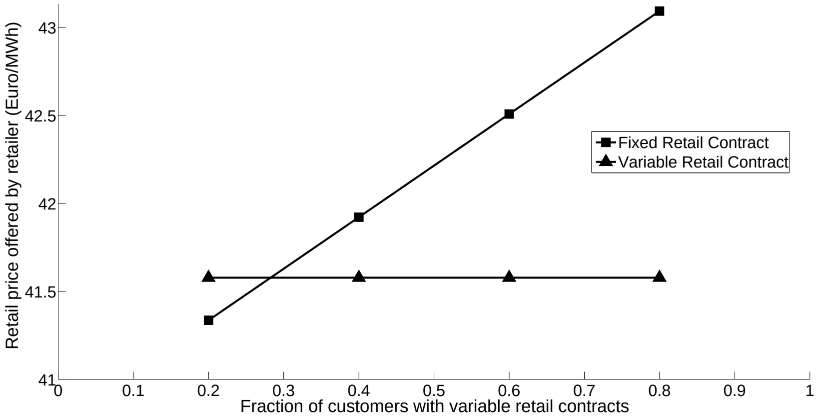


Figure 5.9: Price offered by the retailer with increasing ratio of customers opting for variable retail contracts at 10% EV penetration

#### 5.4.2.5 Savings in charging cost by EV customers

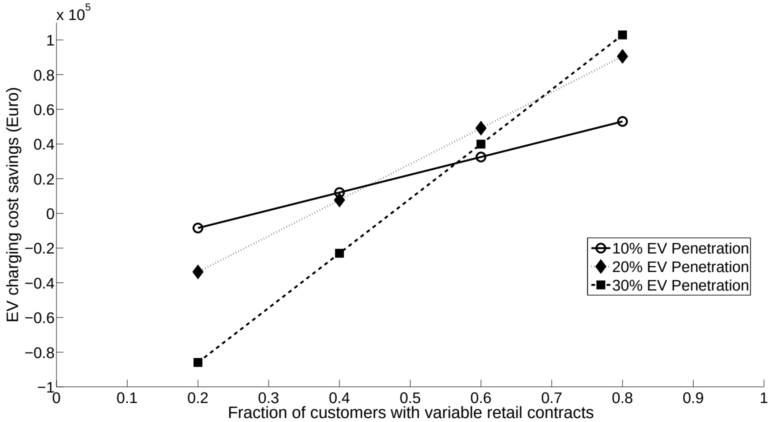


Figure 5.10: EV charging cost savings with increasing variable price contracts

Figure 5.10 shows the total charging cost saving by the EV owners with increasing ratio of the retailer's customers opting for variable price contracts at different levels of EV penetration. The cost savings is calculated as the difference between the costs incurred by EV owners in case they entered a fixed price contract and the costs incurred by them in case they entered into a variable price contract. Considering a pricing structure described in Section 5.3.5, for a lower fraction of customers with variable retail contract, it can be seen that the EV owners would end up paying more by entering into a variable retail contract as opposed to a case when the majority of the retailer's customers have entered into a variable contract. It is interesting to note that this is advantageous to both the retailer and the EV customers because, with variable price contracts, the EV owners would transfer less financial risk to the retailer while attaining additional savings. At the same time, it can be noted that the profits of the retailer would be relatively increased with increasing number of its customers opting for a variable price contract. Additionally, at higher variable price contract ratios, these savings would be increased with increasing levels of EV penetration in the system.

## 5.5 Summary

A stochastic programming based planning model of an electricity retailer that maximizes its expected profit while considering uncertainty in EV charge scheduling has been proposed in this chapter. The solution from the model yielded the forward contract decisions, retail price setting for customers, and the EV demand scheduling. The price setting for retail contracts was determined by the RP model based on two types of contract signed with the retailer. From the case study, it could be concluded that the total cost savings for EV customers would increase with the EV penetration level and also with increasing number of customers opting for variable price contracts with the retailer as opposed to fixed price contracts. This was found to benefit the retailer as its expected profit was found to increase with a greater share of customers opting for variable price contracts. However, it should be mentioned that neglecting power imbalance cost would represent an ideal situation and due to uncertainties involved in customer demand, a more practical approach would necessitate the inclusion of imbalance costs.

# Chapter 6

# Conclusions and Future Work

*This chapter presents the main conclusions from this thesis. Possible ideas for future work that could meaningfully extend the work done in this thesis are also presented.*

## 6.1 Conclusions

In this thesis, mathematical models have been proposed to study the impacts of large scale penetration of grid connected EVs on the demand profile within the test system, price of electricity in the day-ahead and regulating power markets and the changes in regulation cost due to demand response from EVs. Furthermore, a framework for long-term energy portfolio optimization of an electricity retailer, who also assumes the market functions of an aggregaor, has been proposed. The main conclusions from various studies based on developed models are summarize below.

Regarding the effects of EVs on DAM, the following conclusions could be made:

- The proposed JSM assumes that there is a central dispatch of both generators and vehicle batteries thereby resulting in better utilization of both the production resources and consumption side flexibilities. However, this would require changes in the operational structure of current Nordic electricity markets.
- Case studies performed using a Nordic test system indicated that day-ahead price increase due to vehicle integration could be low at lower penetration of EVs. Electricity price increase was found to occur at higher levels of around 75-100 % vehicle penetration, at which point, advanced methods of scheduling of EV charging could be needed to limit the increase.

- Transmission network constraints can directly influence the penetration level of the EVs that can be accommodated in the system before a significant increase in market price. This was observed in the constrained case where power transmission limit between different bidding areas resulted in price leveling within bidding area DK2 at 100% EV penetration when compared to the leveling at 300 % in the unconstrained case.

- Changes in market price are also affected by other factors such as conventional load profile, bidding strategies by various players, state and availability of the production units, intra-area network constraints etc. Hence, more detailed analysis may need to be done in order to observe the effects of these factors on a particular system and arrive at concrete conclusions.

From the case study of EV aggregator participation in RPM, the following points were observed:

- Simulation results indicated that the system could benefit from the aggregated regulating power provided by EVs. The system gain was mostly found to occur in the form of lower regulation costs when EV aggregator bid competitively at lower marginal costs.

- Accounting for the effect of regulating power injection or withdrawal on transmission line losses resulted in a slightly different set of regulating power activation when compared to the merit-order list. The case study with up regulating power scenarios indicated lower regulation costs mostly due to lower up regulating power prices offered by the EV aggregator.

- In the studies performed, it was assumed that the EV aggregator could predict the direction of regulation during a particular delivery hour, which is not entirely accurate. While, there might be indicators that could point to the direction of regulation, predicting it with a high degree of accuracy could prove extremely difficult, if not impossible, in a well functioning market.

- Activation of EVs for power regulation would be very much dependent on the aggregator's position to perform arbitrage just prior to the delivery hour, which is not entirely accounted for and hence, imposes limitations on the results from the study.

- Implementing the proposed activation method for RPM using re-valuation of bids could result in the activation of extremely small power output variations from generators at different buses. This might necessitate automatic control to be implemented by producers and aggregators as opposed to the manual control used today.

Finally, the following inferences could be made from the RP model incorporating EV scheduling:

- The model was found to yield the necessary forward contract decisions, retail price setting for customers with two types of contracts, and EV demand scheduling as outputs. The price setting for retail contracts was assumed to be determined by the retailer based on the type of contract signed.

- An overall conclusion was that the total cost savings of EV owners would increase with EV penetration and also with the increasing number of customers signing variable price contracts with the retailer as opposed to fixed price contracts. This was also found to benefit the retailer, as the retailer's expected profit was found to increase with a greater share of customers opting for variable price contracts.

- The studies performed in this work have not accounted for imbalance costs faced by the retailer. This could have a direct effect on the profit margin of the retailer, the corresponding retail price setting by the retailer and the cost savings of EV owners. Hence, studies accounting for imbalance costs need to be performed to obtain more realistic results.

## 6.2 Future Work

The following ideas regarding electricity markets participation by the aggregator could be identified for future work:

- Aggregator model extension: The functions of the EV aggregator could also be extended to include other types of flexible demand such as electric heating and also DG energy resources such as wind and solar power. The scheduling of EVs could then be performed in a manner so as to maximize the overall benefit for both DG owners and EV owners. Some work regarding the extension of EV aggregator model for scheduling of electric heating energy has been performed in Paper IV listed Chapter 1, Section 1.4.

- Intraday markets: the aggregator has the possibility of trading in the intra-day market such as Elbas that is cleared continuously between the day-ahead market clearing and the delivery hour. If deviations are known prior to the delivery hour, this market could be very valuable in correcting these deviations on time; possibly for a cost lower than that incurred in the regulating power market. It is also possible for the aggregator to perform arbitrage in this market and increase its profits. Further, this continuous market could be used to co-optimize its energy bids in the intra-day and regulating power markets.

- Bilateral contracts: the aggregator can enter into bilateral contracts with wind or solar power producers in order to further hedge against day-ahead and RPM price risks. Additionally, these contracts could also prove useful to internally balance intermittent energy sources by controlling the demand side and reduce imbalance costs incurred by the power producers.

- CfD and Options contracts: the aggregator could also obtain other contracts from the financial electricity market such as CfD to hedge against system-area price difference and options contract to better position itself during demand intensive seasons such as cold winters when the demand is generally high and price volatility and risks are greater.

- Primary and Secondary reserve market: the aggregator could also participate in markets organized by the TSO in order to provide primary and secondary reserves. These reserves could prove useful to improve the frequency quality deterioration caused by large scale integration of uncontrollable sources of power such as wind and solar [88].

With regards to challenges in the distribution network, the following could be addressed as an extension of this thesis:

- Stability enhancement: there could be potential steady-state and dynamic stability issues with large scale integration of new, uncontrolled demand. However, imposing strict grid code requirements on flexible demand [89], similar to conventional generation, could lead to better stability within the system during extreme conditions and also avoid immediate network reinforcements.
- Protection system changes: introduction of distributed generators (DG) and virtual power plants (VPP) such as EV aggregators within the distribution network could lead to bidirectional power flows and hence, increased woes for protection system reliability [90]. Therefore, there is a need for better understanding the problems that could possibly hinder the efficient operation of the protection systems in the presence of DG and VPPs and further suggest relevant mitigating procedures.

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# Appendix

## A. Nordic 32-bus Test System Data

The following tables shows the data used in the case study for the regulating power market [69]. The generator cost is represented using a quadratic function $C_i(P_i) = C_c P_i^2 + B_c P_i + A_c$.

Table A.1 shows the values of generator cost co-efficients $A_c$, $B_c$ and $C_c$ and is obtained from [70]. Table A.2 shows the generator, load and bus data, Table A.3 shows the transmission line related data and Table A.4 shows the transformer data.

Table A.1: Generator Cost Data

| *Bus* | *Ac* | *Bc* | *Cc* | *Plant Type* |
|---|---|---|---|---|
| [No.] | € | €/MWh | €/MW$^2$h | |
| 1012 | 809 | 15.4 | 0.0026 | Hydro |
| 1013 | 1079 | 20.5 | 0.0026 | Hydro |
| 1014 | 925 | 17.6 | 0.0026 | Hydro |
| 1021 | 1076 | 20.5 | 0.0026 | Hydro |
| 1022 | 1619 | 30.8 | 0.0026 | Hydro |
| 1042 | 2226 | 49.2 | 0.00225 | Other Thermal |
| 1043 | 2477 | 54.8 | 0.00225 | Other Thermal |
| 2032 | 809 | 15.4 | 0.0026 | Hydro |
| 4011 | 647 | 12.3 | 0.0026 | Hydro |
| 4012 | 809 | 15.4 | 0.0026 | Hydro |
| 4021 | 1439 | 24.7 | 0.0026 | Hydro |
| 4031 | 1349 | 25.7 | 0.0026 | Hydro |
| 4042 | 2070 | 40.9 | 0.0048 | Nuclear |
| 4047 | 2229 | 44.0 | 0.0048 | Nuclear |
| 4051 | 2070 | 40.9 | 0.0048 | Nuclear |
| 4062 | 3264 | 72.2 | 0.0297 | Coal Fired |
| 4063 | 3264 | 72.2 | 0.0297 | Coal Fired |
| 4071 | 1076 | 20.5 | 0.0026 | Hydro |
| 4071 | 809 | 15.4 | 0.0026 | Hydro |

Table A.2: Generator, Load and Bus Data

| $Bus$ | $P^{max}$ | $P^{min}$ | $Q^{max}$ | $Q^{min}$ | $PL$ | $QL$ | $Nominal$ $Voltage$ |
|---|---|---|---|---|---|---|---|
| [No.] | MW | MW | MVAr | MVAr | MW | MVAr | kV |
| 4011 | 1000 | 0 | 500 | -100 | - | - | 400 |
| 4012 | 800 | 0 | 400 | -160 | - | - | 400 |
| 4021 | 300 | 0 | 150 | -30 | - | - | 400 |
| 4022 | - | - | - | - | - | - | 400 |
| 4031 | 350 | 0 | 175 | -40 | - | - | 400 |
| 4032 | - | - | - | - | - | - | 400 |
| 4041 | 0 | 0 | 300 | -200 | - | - | 400 |
| 4042 | 700 | 0 | 350 | -100 | - | - | 400 |
| 4043 | - | - | - | - | - | - | 400 |
| 4044 | - | - | - | - | - | - | 400 |
| 4045 | - | - | - | - | - | - | 400 |
| 4046 | - | - | - | - | - | - | 400 |
| 4047 | 1200 | 0 | 600 | 0 | - | - | 400 |
| 4061 | - | - | - | - | - | - | 400 |
| 4062 | 600 | 0 | 300 | 0 | - | - | 400 |
| 4063 | 1200 | 0 | 600 | 0 | - | - | 400 |
| 4071 | 500 | 0 | 250 | -50 | 300 | 100 | 400 |
| 4072 | 4500 | 0 | 1000 | -300 | 2000 | 500 | 400 |
| 2031 | - | - | - | - | 100 | 30 | 220 |
| 2032 | 850 | 0 | 425 | -80 | 200 | 50 | 220 |
| 1011 | - | - | 400 | -80 | 300 | 100 | 130 |
| 1012 | 800 | 0 | 400 | -80 | 300 | 100 | 130 |
| 1013 | 600 | 0 | 300 | -50 | 100 | 40 | 130 |
| 1014 | 700 | 0 | 350 | -100 | - | - | 130 |
| 1021 | 600 | 0 | 300 | -160 | - | - | 130 |
| 1022 | 250 | 0 | 125 | -25 | 280 | 95 | 130 |
| 1041 | - | - | - | - | 600 | 200 | 130 |
| 1042 | 400 | 0 | 200 | -40 | 300 | 80 | 130 |
| 1043 | 200 | 0 | 100 | -20 | 230 | 100 | 130 |
| 1044 | - | - | - | - | 800 | 300 | 130 |
| 1045 | - | - | - | - | 700 | 250 | 130 |
| 41 | - | - | - | - | 540 | 128.30 | 130 |
| 42 | - | - | - | - | 400 | 125.67 | 130 |
| 43 | - | - | - | - | 900 | 238.83 | 130 |
| 46 | - | - | - | - | 700 | 193.72 | 130 |
| 47 | - | - | - | - | 100 | 45.19 | 130 |
| 51 | - | - | - | - | 800 | 253.22 | 130 |
| 61 | - | - | - | - | 500 | 112.31 | 130 |
| 62 | - | - | - | - | 300 | 80 | 130 |
| 63 | - | - | - | - | 590 | 256.19 | 130 |

Table A.3: Transmission Line Data

| *FromBus* | *ToBus* | *Line Resistance* | *Line Reactance* | *Line Charging* | *Line Loading Limit* |
|---|---|---|---|---|---|
| [No.] | [No.] | Ohms | Ohms | p.u | MVA |
| 4011 | 4012 | 1.60 | 12.80 | 0.40 | 1000 |
| 4011 | 4021 | 9.60 | 96.00 | 3.58 | 1000 |
| 4011 | 4022 | 6.40 | 64.00 | 2.39 | 800 |
| 4011 | 4071 | 8.00 | 72.00 | 2.79 | 1000 |
| 4012 | 4022 | 6.40 | 56.00 | 2.09 | 1000 |
| 4012 | 4071 | 8.00 | 80.00 | 2.98 | 1000 |
| 4021 | 4032 | 6.40 | 64.00 | 2.39 | 1000 |
| 4021 | 4042 | 16.00 | 96.00 | 5.97 | 1000 |
| 4031 | 4022 | 3.20 | 32.00 | 1.20 | 1600 |
| 4031 | 4032 | 1.60 | 16.00 | 0.60 | 1000 |
| 4031 | 4041 | 4.80 | 32.00 | 2.39 | 1600 |
| 4042 | 4032 | 16.00 | 64.00 | 3.98 | 1000 |
| 4032 | 4044 | 9.60 | 80.00 | 4.77 | 1000 |
| 4041 | 4044 | 4.80 | 48.00 | 1.79 | 1000 |
| 4041 | 4061 | 9.60 | 72.00 | 2.59 | 1000 |
| 4042 | 4043 | 3.20 | 24.00 | 0.99 | 1000 |
| 4042 | 4044 | 3.20 | 32.00 | 1.19 | 1000 |
| 4043 | 4044 | 1.60 | 16.00 | 0.60 | 1000 |
| 4043 | 4046 | 1.60 | 16.00 | 0.60 | 1000 |
| 4043 | 4047 | 3.20 | 32.00 | 1.19 | 1000 |
| 4044 | 4045 | 1.60 | 16.00 | 0.60 | 1600 |
| 4045 | 4051 | 3.20 | 32.00 | 1.20 | 1600 |
| 4045 | 4062 | 17.60 | 128.00 | 4.77 | 1600 |
| 4046 | 4047 | 1.60 | 24.00 | 0.99 | 1000 |
| 4062 | 4063 | 2.40 | 24.00 | 0.90 | 1000 |
| 4071 | 4072 | 2.40 | 24.00 | 3.00 | 1600 |
| 2031 | 2032 | 2.90 | 21.78 | 0.05 | 1000 |
| 1011 | 1013 | 0.85 | 5.90 | 0.13 | 800 |
| 1012 | 1014 | 1.20 | 7.60 | 0.17 | 800 |
| 1013 | 1014 | 0.59 | 4.23 | 0.10 | 800 |
| 1021 | 1022 | 2.54 | 16.90 | 0.29 | 800 |
| 1041 | 1043 | 0.85 | 5.07 | 0.12 | 800 |
| 1041 | 1045 | 1.27 | 10.14 | 0.24 | 800 |
| 1042 | 1044 | 3.21 | 23.66 | 0.57 | 800 |
| 1042 | 1045 | 8.45 | 50.70 | 1.13 | 800 |
| 1043 | 1044 | 0.85 | 6.76 | 0.15 | 800 |

Table A.4: Transformer Data

| *FromBus* | *ToBus* | *Reactance* | *Transformer Nominal Rating* |
|---|---|---|---|
| [No.] | [No.] | p.u | MVA |
| 1011 | 4011 | 0.008 | 1250 |
| 1012 | 4012 | 0.008 | 1250 |
| 1022 | 4022 | 0.012 | 833 |
| 1044 | 4044 | 0.005 | 2000 |
| 1045 | 4045 | 0.005 | 2000 |
| 2031 | 4031 | 0.012 | 833 |
| 4041 | 41 | 0.010 | 1000 |
| 4042 | 42 | 0.013 | 750 |
| 4043 | 43 | 0.007 | 1500 |
| 4046 | 46 | 0.010 | 1000 |
| 4047 | 47 | 0.040 | 250 |
| 4051 | 51 | 0.007 | 1500 |
| 4061 | 61 | 0.013 | 750 |
| 4062 | 62 | 0.020 | 500 |
| 4063 | 63 | 0.010 | 1000 |