Plug-In Electric Vehicle Participation in Electricity Markets A Stochastic Optimization Approach

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Abstract

Government policies for energy efficiency in transportation systems are likely to clear the way for alternative propulsion technologies, such as Plug-in Electric Vehicles (PEVs), to become widespread in automotive industry sales. However, integrating PEVs in electric power systems (EPSs), such that system-favourable charging schedules are facilitated, still poses regulatory and technical challenges for the entire spectrum of stakeholders, from policy makers to regulated distribution system operators and competitive fleet owners. To favour an EPS in question, i.e. a collection of producers, consumers represented by retailers/load aggregators that meet in the electricity market as well as network operators, a combination of competitive market prices as well as regulated use-of-system charges should govern the PEV charging. However, the value proposition, i.e. the value adding services that a Flexible Load Aggregator (FLA) is bringing to the EPS via participating in electricity markets with a contracted fleet of PEVs under Direct Load Control (DLC), remains unclear to this point.

This work-in-progress paper presents a methodology to approximate the economic impact of using a PEV fleet's aggregated battery as a resource in electricity markets, ignoring all network aspects. A stochastic profit optimization of the FLA's self-scheduling is formulated with price taker participation in day-ahead energy and ancillary service markets for capacity. Uncertainty in market prices as well as energy demand is addressed. Using the Conditional Value-at-Risk (CVaR) methodology, risk aversion of the FLA is explicitly captured. The corresponding sensitivity of expected profits is analysed with an efficient frontier. As a result, this model is intended to obtain the optimal PEV charging schedule and according FLA market bids, subject to energy demand requirements for transportation of the final customers. Once the methodology is confirmed, stylized examples and fully fledged case studies can be calculated with the here presented model.

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Notation for Stochastic Programme

The nomenclature used throughout this study is stated below for quick reference: upper case letters are used to denote decision variables, while lower case letters are used to describe input parameters.

Sets and Indices:

$d \in D$	Day types spanning the weekly decision framework
$v \in V$	Vehicles in the considered aggregation
$h \in H$	Time periods spanning the market horizon of one day
$c \in C$	Car types
$f \in F$	Futures contract
$j \in J$	Blocks in the futures contracting curve
$\omega \in \Omega$	Scenarios

Input Parameters

α	Confidence level for the CVaR calculation	[p.u.]
β	Weighting factor of CVaR in objective function	[p.u.]
γ^{ch}	Energy resale price	[€/MWh]
γ^{dch}	Energy discharge compensation price	[€/MWh]
δ	System imbalance, positive in case of excess demand, negative in case of lack of demand	[p.u.]
bc_c	Available battery capacity in a vehicle of class c	[kWh]
c_c	Connection capacity of a vehicle of class c	[kW]
ϑ_c	Driving speed of a vehicle in class c	[km/h]
η_c^{drive}	Driving efficiency of a vehicle in class c	[kWh/km]
η_c^{ch}	*Charging* efficiency of a vehicle in class c	[p.u.]
η_c^{dch}	*Discharging* efficiency of a vehicle in class c	[p.u.]
$vc_{v,c}$	Binary matrix linking vehicle v to a car class type c	$\in \{0; 1\}$

Futures Price Curve

$\lambda_{f,j}^F$	Futures market price of block j in contracting curve of future f	[€/MWh]
$\bar{E}_{f,j}^F$	Upper limit of futures block j for contract f	[MWh]

Stochastic Market Prices

π_ω	Probability of scenario ω	[p.u.]
$\lambda^{DAM}_{d,h,\omega}$	Day-ahead market price in time period h of day d and scenario ω	[€/MWh]
$\varrho^{+}_{d,h,\omega}$	Ratio between positive imbalance price and day-ahead market price in time period h of day d and scenario ω	[p.u.]
$\varrho^{-}_{d,h,\omega}$	Ratio between negative imbalance price and day-ahead market price in time period h of day d and scenario ω	[p.u.]

Stochastic PEV Fleet Mobility

$av_{d,v,h,\omega}$	Binary fleet availability matrix of indicating the connection of vehicle v in hour h of day d and scenario ω	$\in \{0;1\}$
$\nabla_{d,v,h,\omega}$	State-of-Charge loss resulting due to the previous trip's driving for vehicle v in hour h of day d and scenario ω	[kWh]
$isoc_{0,v,0,c}$	Initial state-of-charge of vehicle v prior to optimization horizon	[kWh]

Positive Real Decision Variables

First Stage Decision

$E^{F}_{h,f,j}$	Energy corresponding to hour h bought in the futures market from contract f in block j	[MWh]

Second Stage Decision

$E^{DAM,\,ch}_{d,h,\omega}$	Energy as a *buying* position in the day-ahead market in hour h of day d and scenario ω	[MWh]
$E^{DAM,\,dch}_{d,h,\omega}$	Energy as a *selling* position in the day-ahead market in hour h of day d and scenario ω	[MWh]

Third Stage Decision

$\Delta^{+}_{d,h,\omega}$	*Positive* energy deviation, balancing close to real time in hour h of day d and scenario ω	[MWh]
$\Delta^{-}_{d,h,\omega}$	*Negative* energy deviation, balancing close to real time in hour h of day d and scenario ω	[MWh]
$E^{RT,\,ch}_{d,v,h,\omega}$	Net real time energy *bought* from market and sold to vehicle v for *charging* in hour h of day d and scenario ω	[kWh]
$E^{RT,\,dch}_{d,v,h,\omega}$	Net real time energy *sold* from market and bought to vehicle v for *discharging* in hour h of day d and scenario ω	[kWh]
$SOC_{d,v,h,\omega}$	Battery state-of-charge of vehicle v for *discharging* in hour h of day d and scenario ω	[kWh]

Risk Measure

ζ	Auxiliary variable used to calculate the CVaR	[€]
$\imath_{\omega}$	Scenario-specific auxiliary variable used to calculate the CVaR	[€]

1 Introduction

1.1 Literature Review and Contributions

In a regulatory framework of modern, unbundled and deregulated electric power systems, the key component in optimal plug-in electric vehicle charging should be market driven. A PEV aggregation agent should hence have an objective function that is consistent with other agents known in electric power systems. Reviewed literature has dealt with electricity market participation, which usually involves the explicit modelling of uncertainty and risk aversion.

Consider therefore the problem of an electricity retailer that intends to aggregate a PEV use as a resource in electricity markets. The operational challenge of such a PEV Aggregator presents a combination of the classic problems of a retailer (sometimes also referred to as supplier or marketer) [5], a large consumer (with potential on-site generation) [6], and a conventional power producer with resource unavailability [17, 16], as well as of an energy storage system (ESS) operator.

The primary goal of the retailer, as an intermediary between producers and consumers [6], is the medium term procurement of energy in electricity markets for a subsequent resale to final customers at an agreed price. The main source of profit for a retailer is the difference in procurement cost and resale revenue. Typically, retailers cover a large amount of energy demand in the futures market and procure the rest from short-term pool markets. In short, the retailer buys electricity at an uncertain price and resells it to an uncertain demand [5].

The main objective of a producer is to sell its available energy and capacity in the futures, pool and ancillary service markets. The futures market provides fixed prices through futures contracts over a pre-defined time horizon, while pool prices allow the producer to sell energy at higher prices in the short term. Reserve being an important product to guarantee sufficient generation capacity available in the electric power system to assure short term functioning, presents a valuable opportunity to fast response equipment. Balancing energy is an important tool for readjusting previous market commitments closer to real time. If the production of this agent is subject to some technical constraints and bound to suffer from unavailability, the producer may have to procure energy in the pool to meet the futures contracting obligations[17]. The problem of resource unavailability becomes even more prevalent if the production stems from vRES such as uncontrollable win power production. A detailed modelling of a wind power producer participating in short term electricity markets under uncertainty and risk aversion is found in [16]

However, there is not only similarity with known problems considering electricity market involvement, the following basic aspects differentiate the conventional agents and the new PEV aggregation agent, namely: demand is set via consumption of vehicles , consumption as well as the unavailability of an aggregated battery is defined by the mobility of the vehicles. Therefore modelling of mobility is crucial and identified as a key element for classifying existing literature.

[2] model a similar problem, of an storage owner scheduling capacity in balancing markets to compensate uncertainty in wind availability, however it can be assumed that the owner of the wind farm is also the owner of the ESS.

Most recently [1] performed a simulation investigating the potential role of PEV in the UK electricity network with balancing requirements electricity network with a high shares of variable renewable energy sources (vRES) such as wind. The study employs stochastic trip generation profiles.

1.2 Main Research Question

- The objective of this study is to analyse, how electricity price uncertainty and mobility-caused unavailability of aggregated PEV batteries affect the optimal market involvement and profit functions of this new agent.

This study seeks to find insights about, e.g.:

1. Are aggregated vehicle batteries likely to present a physical hedge against price risk compared to other risk hedges.

2. What is the dominating of the inherent characteristic of PEV storage: flexibility and unavailability? The flexibility of the storage may – even though subject to conservative capacity connection constraints – over-compensate the risk of unavailability.

2 Uncertainty Characterization

There are two main sources of uncertainty discussed in this study of a PEV aggregator taking decisions in electricity markets: market price uncertainty and uncertainty about resource availability. The former, market price uncertainty, is a known subject of research, and includes forecasting of futures prices as well as pool prices, i.e. day-ahead, regulation, adjustment and balancing market prices among others. The latter, resource availability of a fleet of vehicles remains largely underdeveloped. Characterising it, boils down to analysing the stochastic processes that determine the mobility of each vehicle in the fleet, i.e. the trips traveled, during which the vehicles are unavailable because they are disconnected. In the following, both sources of uncertainty are discussed, the former only shortly, the latter in greater detail.

Characterizing Electricity Market Price Uncertainty

Time series analyses have proven in various studies to be a very convenient instrument to forecast for instance day-ahead market clearings in a pool. The challenge lies in capturing characteristics such as daily and weekly seasonalities, high frequency and high volatility. Especially irrational bidding behaviour by market agents, make price series more volatile than for instance demand series [?].

Estimating parameters of auto-regressive integrated moving average (ARIMA) models, is well described by [14, 4]. ARIMA relate current prices to past prices and current errors to past errors. They can be characterized by (p, d, q) corresponding to the number of autoregressive terms, the differencing order, and the number of moving-average terms, respectively, while SARIMA models include differencing for the daily or weekly seasonality. This study uses the notation from [7], given by $SARIMA(p, d, q) \times (P, D, Q)_S$:

$$\left(1-\sum_{j=1}^{p}\phi_j B^j\right)\left(1-\sum_{j=1}^{P}\Phi_j B^j\right)(1-B)^d\left(1-B^S\right)^D y_t=\left(1-\sum_{j=1}^{q}\theta_j B^j\right)\left(1-\sum_{j=1}^{Q}\Theta_j B^j\right)\varepsilon_t$$

with a seasonal component of P autoregressive parameters $\Phi_1, \Phi_2..., \Phi_P$, Q moving average parameters $\Theta_1, \Theta_2, ..., \Theta_Q$ and a differentiation order D.

Mobility and Uncertainty of Fleet Unavailability

If historical time series data of fleet movement were available, the standard procedure as proposed in [8] could be applied following the subsequent steps:

1. The fleet movement, i.e. the amount of connected/disconnected vehicles, is considered as a stochastic process being a random variable that evolves over time.

2. Applying a transform of the time-based observations to the frequency domain and choosing an appropriate histogram representation (i.e. number of bins and mass centers of the chosen classes) to produce an adjusted probability density function (pdf).

3. The pdf is then fitted to another, well known continuous probability distribution (Weibull, Poisson, bimodal normal, or exponential etc.) to use the estimated parameters for an analytical construction of a cumulative probability distribution function (cdf).

4. To assure that the normality assumption needed to apply ARMA models, i.e. a necessary Gaussian nature of the marginal distributions, to hold, the original cdf is analytically transformed to normal.

5. If multiple fleet movements, i.e. sub-groups of the total fleet in one geographical area are modeled, one could assume that the unavailability of one spot is physically related to its neighbors. In that case the underlying stochastic processes for fleet unavailability would be dependent and therefore Cholesky decomposition and cross-correlation of the simulated normal errors would have to be applied to the resulting *transformed* series.

6. A normality plot of the transformed data can be performed to test the goodness of fit.

7. Finally the autocorrelations inferred from historical data series are modeled by adjusting univariate ARMA models.

However, the available data do not include historical time series of connected and disconnected vehicles. Therefore scenario generation is performed constructing mobility patterns based on available data from household travel surveys, such as the US *National Household Travel Survey* (NHTS) or, as in this study, the German *Mobilität in Deutschland* (MID) [11]. From selected German respondents, who are most likely to adopt electric vehicles [3], it is assumed that there exist information on:

- The expected number of trips for each of the moving vehicles on a given day ntr_d^{avg}, as depicted in Tab. 6 of the Appendix, and
- Vehicle specific expected constant trip speeds ϑ_c to calculate trip durations given the distance.

For modeling the fleet unavailability, mainly three types of information were obtained, given by [?] in the form of discrete cdfs , which are all detailed in Tab. 7, Tab. 8 and Tab. 9, respectively, of the Appendix:

- The probability of travel on a certain day d, $\pi_d^{travel} = \hat{\pi}_d^{travel}$.
- The probability of starting a trip on a specific day d and hour h, $\pi_{d,h}^{startH} = \sum_{j=1}^{4} \hat{\pi}_{d,t\cdot 4-j}^{startH}$.
- The probability of a trip to be of a certain length l on a specific day $\pi_{d,l}^{range} = \hat{\pi}_{d,l}^{range} - \hat{\pi}_{d,l-1}^{range}$,

where the week is represented by a set of typical days with similar characteristics, i.e. $d \in \{Monday, Weekdays, Friday, Saturday, Sunday\}$, the time slots resolve the day in 24 hours, $h \in \{1, 2, ..., 24\}$, and the trip lengths l are sorted into 20 different classes with increasing intervals between class centers. Hats, $\hat{}$, refer to the original unchanged data from [10], $\pi_{d,t}^{start}$ is aggregated from original t 96 15-Minute to 24 hourly data points and $\pi_{d,l}^{range}$ is transformed from original cdf to adjusted pdf. For details please refer to the Appendix.

However detailed the data is provided in the cited sources, the exact process of creating the cdfs is not given in a sufficiently detailed manner. The lack of raw data makes testing for statistical dependencies of the underlying random variables impossible to this point. It seems, however, that the given cdfs are mere histograms of all observations within the filtered group of vehicles, and intuition permits to suspect a high statistic dependence of for instance start times and trip lengths.

Algorithm for Mobility Scenario Generation The goal of the algorithm for mobility scenario generation is to combine the information given by the probability of *any car* to be traveling at a certain time and day for a certain distance. This process boils down to creating probable scenarios for the unavailability of the entire fleet in terms of connected and disconnected vehicles.

Therefore the following assumptions are made:

- Suppose there are $|H|$ hours in a day, $|T|$ trips made by each car on a certain day and there are $|V|$ vehicles under direct load control of the aggregator, where h stands for the hour, t for trips and v indicates the index of the vehicle.
- Each vehicle belongs to a certain type of car indexed by c and there are $|C|$ types of cars characterized by
  - available battery capacity bc_c [kWh]
  - connection capacity c_c [kW]
  - normal driving speed ϑ_c [km/h]
  - driving efficiency η_c^{drive} [kWh/km]
  - charging efficiency η_c^{charge} [p.u.]

Then a binary matrix $vc_{v,c}$ of dimensions $|V| \times |C|$ can be constructed indicating whether a certain vehicle belongs to a car class type $vc_{v,c} = 1$, or not $vc_{v,c} = 0$. This will be helpful indicating the linear programme the activation of certain constraints with car class specific data.

In the following we denote the stochastic processes and their scenario representations coherently with [7] as follows. A stochastic process $\lambda^i : i \in \{travel, startH, range\}$ is given by vectors $\lambda^i(\omega^i), \omega^i = 1, ..., |\Omega^i|$, where ω^i is the scenario index and Ω^i is the number of scenarios considered. $\lambda^i_{\Omega^i}$ are the sets of possible realizations of stochastic processes λ^i, i.e., $\lambda^i_{\Omega^i} = \left\{\lambda^i(1), ..., \lambda^i(\Omega)\right\}$. Each realization $\lambda^i(\omega^i)$ is associated with a probability defined as

$$\pi^i(\omega) = P\left(\omega | \lambda^i = \lambda^i(\omega)\right) \text{ with } \sum_{\omega \in \Omega} \pi^i(\omega) = 1. \tag{1}$$

Random realizations of the respective stochastic processes and assuring the feasibility of consecutive trips, the result of the algorithm for mobility scenario generation provides two matrices, which define a mobility scenario: the availability matrices on a daily $trv_{d,v}$, and hourly $av_{d,v,h}$ basis[1], as well as the SOC loss matrix $\nabla_{d,v,h}$. An initial state of charge of the vehicles needs to be provided separately.

2.1 Importance of considering Stochasticity in Mobility

The importance of considering stochasticity in a PEV scheduling optimization problem can be explained by the amount of uncertainty in crucial input data. Figures 1 and 2 show graphical illustrations of resulting connection / disconnection as well as SOC reductions over time from the mobility scenario generation algorithm described above for 50 vehicles and 1000 scenarios. The standard error bars allude to the order of magnitude in which input data for optimization problems can vary for the same day and hence, in how far these variations may impact the optimal scheduling outcome as well as influence on profit distributions his may yield.

However, the detailed description of the algorithm to generate scenarios of the mobility and according unavailability of the PEV batteries as a resource for transactions in electricity markets can be seen in the Appendix.

3 Decision Framework

3.1 Market Involvement

With reference to the description of a fully fledged electricity market organization in [7], we are modeling the typical decision framework for a PEV aggregator as a big consumer/retailer. Such an

[1] $trv_{d,v}$ and $av_{d,v,h}$ are consistent with respect to each other, i.e they contain the same information in different time resolutions.

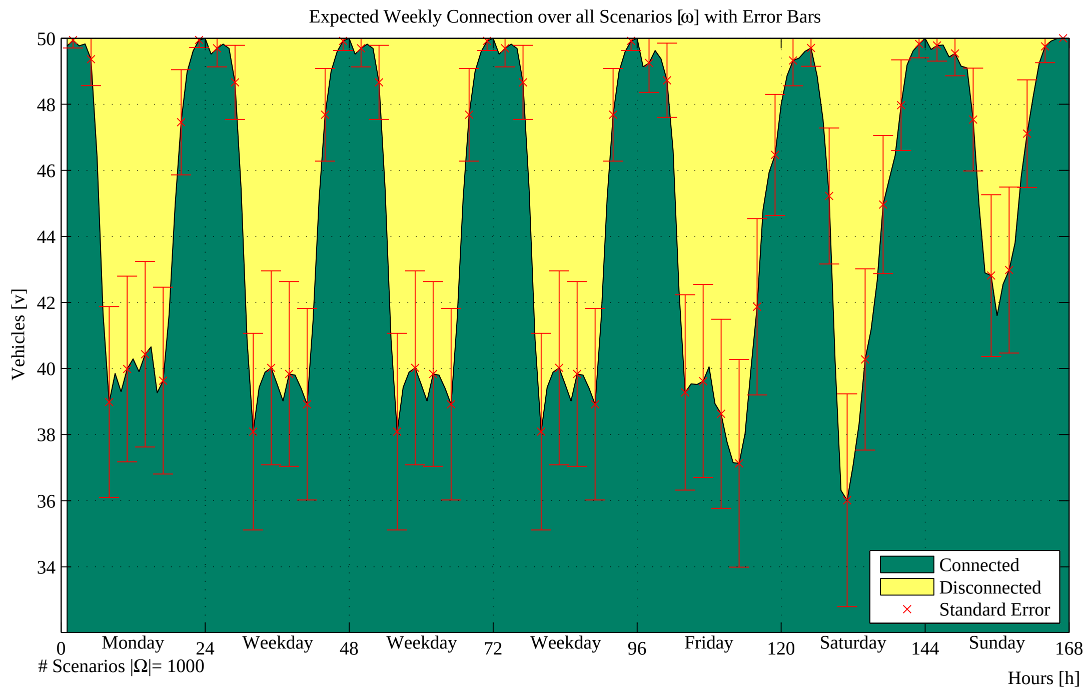


Figure 1: Uncertainty of Mobility Inputs: Graphical Illustration of Connection & Disconnection Over Time with Standard Error Bars over 1000 Scenarios

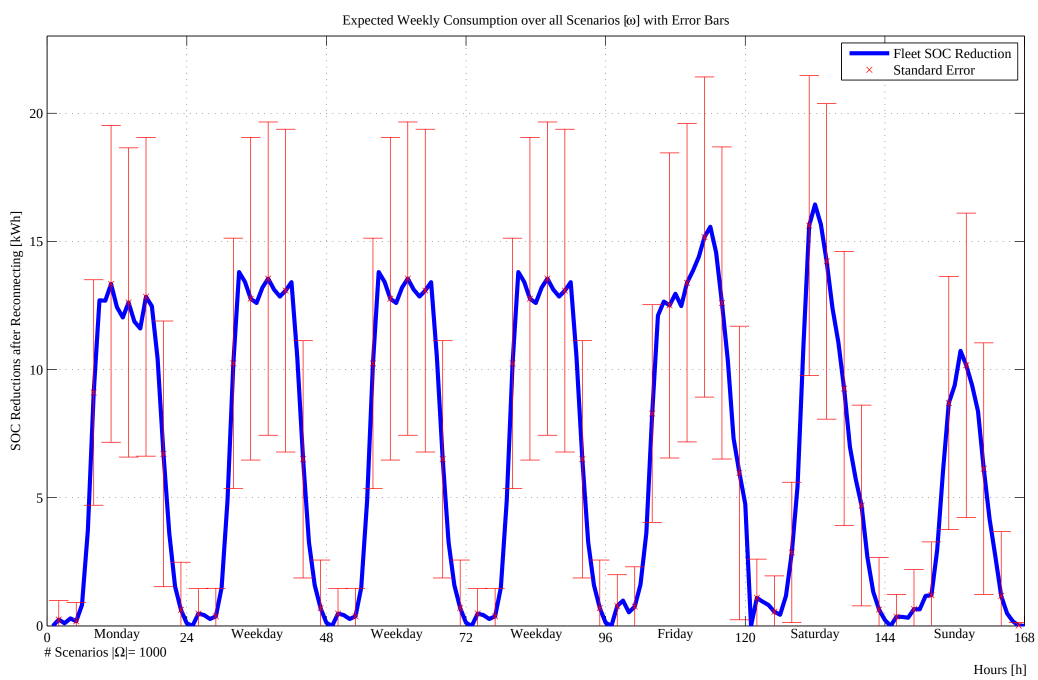


Figure 2: Uncertainty of Mobility Inputs: Graphical Illustration of Aggregated SOC reductions over Time with Standard Error Bars over 1000 Scenarios

agent would intend to determine its optimal involvement in the futures market to hedge against pool (day-ahead and adjustment/balancing markets) price volatility on the one hand and use adjustment and balancing market clearing close to real time for adjusting previous commitments, depending on the unavailability of its aggregated resource. Hence, without loss of generality we consider a decision sequence of the PEV aggregator as follows:

1. On a weekly basis the considered PEV aggregator decides on futures contracts spanning one week to be negotiated in the futures market.
2. Every day the PEV aggregator decides its bidding in terms of pool involvement, which for simplicity we reduce to sequential clearings of:
   (a) day-ahead, and
   (b) balancing markets.

Please note, that even though a PEV aggregator does present a controllable/flexible load we explicitly do not capture its potential involvement in the reserve and the regulation markets, as currently it remains unclear, if the fast response equipment needed for such involvement can be economically justified.

Firstly, decisions related to weekly futures contracting are taken prior to knowing the market outcome of the subsequent clearings, i.e. up to $h_{d1}^{DAM} - 1$, one hour prior to the first day-ahead market clearing of the week. Secondly, decisions considering day-ahead market bids have to be taken. The day-ahead market covering energy transactions, which are effective during the whole day d, is cleared at a certain hour $h^{DAM}$of day $d-1$, i.e. up to $N_h - h^{DAM} + N_h$ hours prior to the respective real time period. This, in fact, is the justification for adjustment and balancing markets which allow the market agents to carry out corrective transactions in the form of last-minute energy adjustments to meet the futures and day-ahead market commitments and from a system perspective to guarantee the real time energy balance between generation and demand. This third market in the here presented decision framework is cleared slightly before each period h of day d. It is herein assumed that the balancing prices as well as the resource unavailability are perfectly known to the decision maker at t^B, the time of trading in the balancing market for the following hour. In Fig. 3 a description of the sequential market clearings in a weekly market horizon are given in the form of a time line diagram.

Hence, the decisions taken by the PEV aggregator can be categorised according to their nature and sequence: there are here-and-now as well as wait-and-see decisions, which can be made at a first, second or third stage.

Here-and-now decision:

- First stage:
  - Futures Contracting: The PEV aggregator can take a decision on the amount of energy procured through futures

Wait-and-see decisions:

- Second stage:
  - Day-ahead market decisions: The aggregator can decide the offer curve to be submitted to the day-ahead market operator specifying energy prices and quantities of energy, i.e. when to produce and when to consume.
  - Third stage:

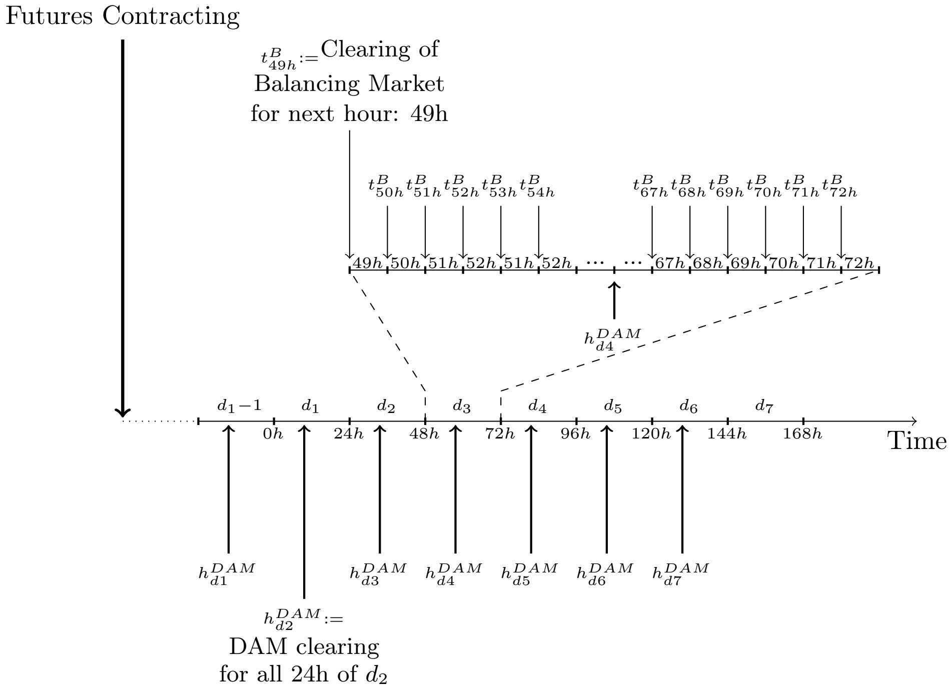


Figure 3: Market Clearing Structure

- ∗ The day-ahead prices as well as the balancing prices materialised as well as the perfect information about the vehicle availability, the PEV aggregator can take adjustment/balancing market decisions: Decisions are related to the real time consumption/production of each vehicle which translates into the deviations from the energy trading commitments in the previous markets.

By means of constructing a scenario tree, Fig. 4 illustrates the sequential decisions an aggregator takes in the above described decision and market framework.

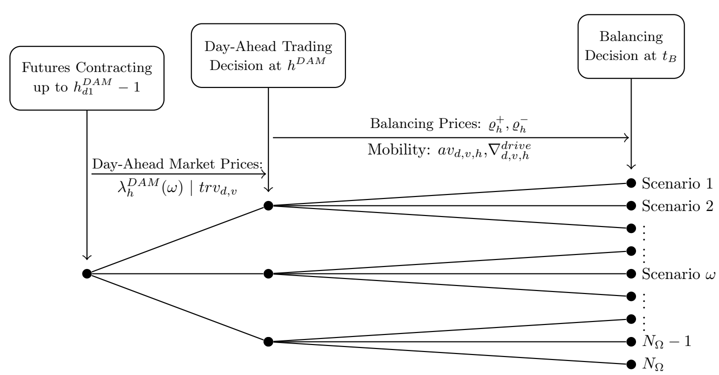


Figure 4: Scenario Tree: PEV Aggregator in Sequential Markets

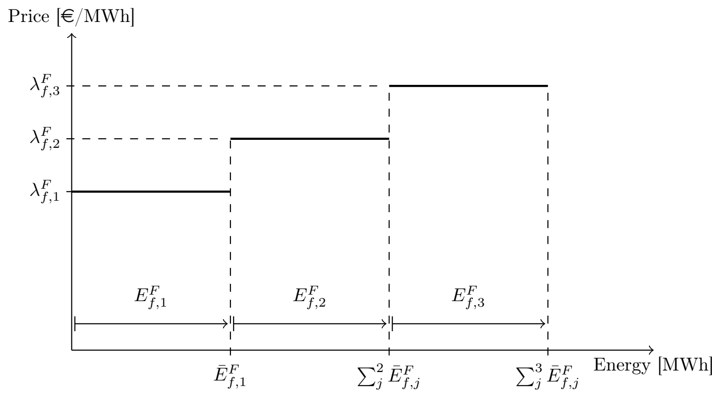


Figure 5: Forward Contract Buying Curve as in [?]

Price Taker in Futures Market

For the purpose of this study, it is reasonable to consider a medium size PEV aggregator to make an impact on the futures market pricess. Hence, it is made use of futures contracting curves to model the price impact of the producer on the futures market as a price maker. A futures contracting curve depicts the variation in the price with the amount of power traded similar to an inverse demand function. We use the formulation presented in [5] to model the purchasing cost for energy in period h as follows:

$$C^F_{d,h} = \sum_{f \in F_{d,h}} \sum_{j \in J} \lambda^F_{f,j} \cdot E^F_{h,f,j}, \ \ \forall d, h. \tag{2}$$

Subject to:

$$E^F_{h,f,j} \leq \bar{E}^F_{f,j}, \ \ \forall h, \forall f, \forall j, \tag{3}$$

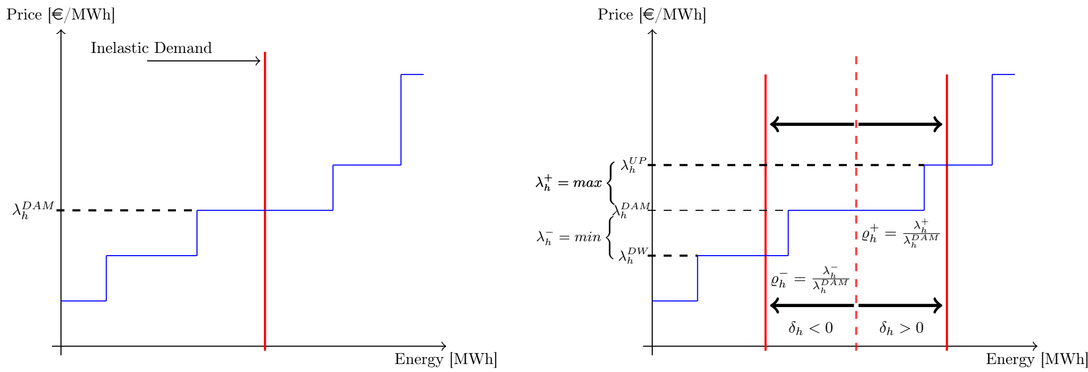
$$E^F_f = \sum_{j \in J} E^F_{h,f,j}, \ \ \forall f, \tag{4}$$

where $F_{d,h}$ is the set of futures contracts available in period h of day d, $E^F_{h,f,j}$ is the energy bought from block j of contracting curve for future f. Constraints, 3and 3 assure that maximally the available energy is bought and that for contrac f this is equal to sum of the energy bought all blocks j. A visualization of this futures buying curve can be found in Fig. 5 .

3.2 Deviations in the Balancing Market

Theoretically, balancing markets should be cleared as close as possible to the period of physical energy delivery so that as precisely as possible the available production means and the actual consumption needs are known. A very good example for this is the Australian Market Design. In this study it is therefore assumed that every PEV aggregator would attend the balancing market with perfect information on its availability of the PEV fleet. Any market agent expecting a final production below or above the last energy schedule resulting from trading in the DAM is commanded to amend its energy deviations in the balancing market.

System Imbalances, $\delta \neq 0$, can be positive or negative. Here ***negative*** energy deviation, $\delta < 0$ is a lower system consumption (or higher system production) than scheduled. A ***positive*** deviation, $\delta > 0$, analogously vice versa. The formulation for the balancing prices is similar to [?], expressed as a linear combination of positive and negative imbalance price ratios**:**



(a) Day-Ahead Price Formation

(b) Imbalance Price Formation

Figure 6: Market Mechanisms

$$\varrho_h^+ = \frac{\lambda_h^+}{\lambda_h^{DAM}}, \quad (5) \qquad\qquad \varrho_h^- = \frac{\lambda_h^-}{\lambda_h^{DAM}}, \quad (6)$$

where λ_h^+ and λ_h^-, refer to the balancing market prices. By this definition, negative deviations Δ_h^- are priced with λ_h^-, which is only different from the day-ahead market price λ_h^{DAM} in case of $\delta < 0$. Accordingly, positive deviations Δ_h^+ are weighted with the price for positive imbalances λ_h^+, which is only different from the day-ahead market price λ_h^{DAM} in case of $\delta > 0$. This effectively means that, when positions from the previous market have to be balanced, the balancing responsible party, here the PEV aggregator can at the most as well off as it would have been trading all energy day-ahead, when the system imbalance has the opposite sign compared to its own deviations. In case the own deviation contributes to the system imbalance it is penalized by paying a higher price for purchases or selling at a lower price for generation.

The formulation in [16], treating a wind power producer in sequential markets, is different to the here presented one. It is modelling a net producer and energy positions are always selling in the market, while in this formulation they are net buying positions, i.e. Δ is of opposite sign. The market mechanisms that drive the formation of the prices are illustrated in Fig. 6 .

4 PEV Aggregator Model

4.1 Market Involvement and Sales Revenue

The PEV aggregator and its energy storage represents a trader in the markets, buying and reselling energy. Leaving the futures market aside for a moment and for simplicity let us assume the day-ahead and balancing markets can be simplified to one pool price λ_h^{pool}. The PEV aggregator, not withstanding that over all time periods it consitutes a net load to the system, it has two possible decision alternatives for each time period h:

1. The aggregator can act as a demand consuming energy and having a net buying position in the pool, or

2. it can act as a generator producing energy and having a net selling position in the pool,

where its pool involvement in period h is a continuous, i.e. positive for buying/consuming and negative for selling/producing energy, variable denoted E_h^{pool}. In the first case the aggregator buys energy in the pool at price λ_h^{pool} and resells it to its PEV clients for *charging* their batteries at an energy price, which subsequently shall be called γ^{ch}. Even though this price could have different time resolutions imaginable[2], for simplicity and without loss of generality, it here is represented as a constant energy price throughout the entire time horizon. Hence the PEV aggregator's revenue in time period h is then:

$$E_h^{pool} \cdot \left(\gamma^{ch} - \lambda_h^{pool}\right). \tag{7}$$

In the second case however, it buys energy from its clients, which is then sold in the pool. It is sensible to assume that the price for *discharging* energy, which subsequently shall be called γ^{dch}, is significantly higher than γ^{ch}, because it is sensible to assume that the reservation price of energy lies above the cost of charging the battery and using the PEV clients' battieres for discharging has a - potentially prohibitively burdensome - cost of degradation. This cost is usually modelled as a function of the depth of the discharge, however this study does not go into the details of costs stemming from battery capacity degradation and hence simplifies this cost to a constant monetary unit per discharged energy value, which, besides energy, is the second component of γ^{ch}. Nevertheless, the revenue of the aggregator with a net selling position in the pool in time period h is then:

$$E_h^{pool} \cdot (\gamma^{dch} - \lambda_h^{pool}). \tag{8}$$

If, for computational reasons, the continuous character of the pool involvement is relaxed and E_h^{pool} accordingly split up in two non-negative components, one in case of a buying $E_h^{pool,\,ch}$ and one in case of a selling $E_h^{pool,\,dch}$ position, such that the linear expression holds: $E_h^{pool} = E_h^{pool\,ch} - E_h^{pool\,dch}$. Then, the sales revenues of Eq. (7) and Eq. (8) can be jointly described by:

$$E_h^{pool,\,ch} \cdot \left(\gamma^{ch} - \lambda_h^{pool}\right) + E_h^{pool,\,dch} \cdot \left(\lambda_h^{pool} - \gamma^{dch}\right), \tag{9}$$

as in the presence of charging and discharging inefficiencies η^{ch}, η^{dch}, the two addends of Eq. (9) are only nonzero in the same period h for sub-optimal solutions of the profit maximisation problem.

Continuing to relax simplifying assumptions, let the pool prices and energy quantities now be differentiated into components of the sequential markets. Consistently, λ_h^{DAM} denotes the price, $E_h^{DAM,\,ch}$ and $E_h^{DAM,\,dch}$ the non-negative energy quantities in case of a buying and selling position committed in the day-ahead market, respectively. Note that, again the linear expression $E_h^{DAM} = E_h^{DAM,\,ch} - E_h^{DAM,\,dch}$, holds. Furthermore, let E_h^{RT} be the real time, physical energy delivery in period h. Then, the total deviation between day-ahead market and balancing market can be denoted by $\Delta_h = E_h^{RT} - E_h^{DAM}$. In other words, for instance if at the time of the physical delivery energy consumption is greater than the previously committed buying position in the day-ahead market, there is a positive deviation, which has to be balanced via purchases. There are more possible cases however. Therefore, the continuous variable Δ_h again is expressed by a linear combination of positive and negative deviations: $\Delta_h = \Delta_h^+ - \Delta_h^-$. Hence the following logical equivalence:

$$\begin{aligned} \Delta_h \quad &= \quad E_h^{RT} \quad - \quad E_h^{DAM} \\ \iff (\Delta_h^+ - \Delta_h^-) \quad &= \quad \left(E_h^{RT,ch} - E_h^{RT,dch}\right) - \left(E_h^{DAM,\,ch} - E_h^{DAM,\,dch}\right), \end{aligned} \tag{10}$$

which allows $2^3 = 8$ different combinations of the three addends (ignoring the do-nothing cases for which either of the three addends is zero). Tab. 1 and Fig. 7 visualise the 6 possible system outcomes. Note that combinations *iii* and *vi* are infeasible and already covered by combinations *iv* and *vii*, therefore they are cancelled out.

[2]Possible designs include: flat energy tariff, two-, or three-step time-of-use, hourly varying, at the highest the time resolution of the pool price representation, or if indexed to pool price, an (expected) market price plus fee.

combinations	Δ_h	E_h^{RT}	E_h^{DAM}
i	$+$	ch	ch
ii	$-$	ch	ch
~~iii~~	~~$+$~~ $\rightarrow -$	dch	ch
iv	$-$	dch	ch
v	$+$	ch	dch
~~vi~~	~~$-$~~ $\rightarrow +$	ch	dch
vii	$+$	dch	dch
$viii$	$-$	dch	dch

Table 1: Case Table and Resulting Deviations

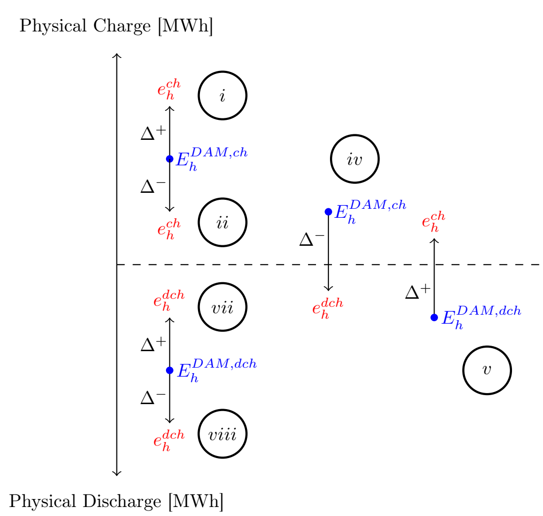


Figure 7: Graphical Visualisation of Possible Deviations

4.2 Expected Profit

As stated above, the objective of the PEV-aggregator is to maximise its expected profits from trading energy in the above mentioned trading floors: Futures, Day-ahead and Balancing Market, to sell and resell it to its clients in real time. In the following the expected profit is broken down by market involvement and energy exchanging entity.

Expected Profit from Day-Ahead Market Transactions

The formulation for the expected profit from day-ahead market transactions for every period h and every day d in a scenario probability weighted sum of differences in selling (revenue) and buying (cost) position, in terms of energy quantities, multiplied by the day-ahead market prices over all scenarios, is hence:

$$
\begin{aligned}
& \mathbb{E}\left\{\Pi_{\omega}^{DAM}\right\} \\
= & \textstyle\sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H} \quad \pi_{\omega}\cdot \quad \Pi_{d,h,\omega}^{DAM} \\
= & \textstyle\sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H} \quad \pi_{\omega}\cdot\left[E_{d,h,\omega}^{DAM}\cdot\lambda_{d,h,\omega}^{DAM}\right] \\
= & \textstyle\sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H} \quad \pi_{\omega}\cdot\left[\left(E_{d,h,\omega}^{DAM,dch}-E_{d,h,\omega}^{DAM,ch}\right)\cdot\lambda_{d,h,\omega}^{DAM}\right].
\end{aligned} \tag{11}
$$

In day-ahead electricity markets it is common to submit not only one single energy quantity which as a consumer (producer), one is willing to buy (sell) in a given time period h. Rather, a stepwise block curve of maximum (minimum) buying (selling) prices as a function of the corresponding energy quantities. Offers for selling are usually commanded to be of a non-decreasing nature [13], while it is supposed that bids for buying energy have to be non-increasing. In the here described stochastic program of a PEV aggregator's profit on day d, obviously, different scenarios of day-ahead prices, $\left\{\lambda_{d,h,1}^{DAM},\lambda_{d,h,2}^{DAM},\ldots,\lambda_{d,h,N_{\Omega}-1}^{DAM},\lambda_{d,h,N_{\Omega}-1}^{DAM}\right\}$ result in different day-ahead market involvements $\left\{\left(E_{d,h,1}^{DAM,\,ch}-E_{d,h,1}^{DAM,\,dch}\right),\left(E_{d,h,2}^{DAM,\,ch}-E_{d,h,2}^{DAM,\,dch}\right),\ldots,\right.$ $\left.\left(E_{d,h,N_{\Omega}-1}^{DAM,\,ch}-E_{d,h,N_{\Omega}-1}^{DAM,\,dch}\right),\left(E_{d,h,N_{\Omega}}^{DAM,\,ch}-E_{d,h,N_{\Omega}}^{DAM,\,dch}\right)\right\}$, which can represent either a buying or a selling position. It is therefore reasonable to enforce two additional constraints, (12) and (13), to assure that the bidding in the day-ahead market fulfills the above described requirements:

$$
E_{d,h,\omega}^{DAM,\,dch} \leq E_{d,h,\omega'}^{DAM,\,dch}, \quad \forall d,h,\ \forall\omega,\omega' : O^{DAM}(d,h,\omega)+1=O^{DAM}(d,h,\omega'), \tag{12}
$$

$$
E_{d,h,\omega'}^{DAM,\,ch} \leq E_{d,h,\omega}^{DAM,\,ch}, \quad \forall d,h,\ \forall\omega,\omega' : O^{DAM}(d,h,\omega)+1=O^{DAM}(d,h,\omega'). \tag{13}
$$

$O^{DAM}$is used to sort the day-ahead prices associated with each period in an increasingly manner for each scenario ω. Therefore, element $O^{D}(d,h,\omega)$ represents the position of day-ahead price $\lambda_{d,h,\omega}^{DAM}$ over all scenarios $\omega\in\Omega$. If this price is the smallest one, then $O^{D}(d,h,\omega)=1$. On the contrary, if $\lambda_{d,h,\omega}^{DAM}$ corresponds to the largest price, $O^{D}(d,h,\omega)$ is equal to the number of different day-ahead prices in period h. Considering a given time period, identical day-ahead prices are associated with equal values in the matrix O^{DAM}, i.e. if $\lambda_{d,h,\omega}^{DAM}=\lambda_{d,h,\omega'}^{DAM}$ then $O^{D}(d,h,\omega)=O^{D}(d,h,\omega)$.

The same justification for constraints similar to (12) and (13) could be given for the subsequent balancing market. However, since the focus of this research lies on finding the optimal DAM offers and bids for the PEV aggregator, the simplification of single optimal energy quantities in the subsequent balancing markets is chosen.

Finally the non-anticipativity constraints (14) and (15) ensure that, those scenarios that share a common history up until the DAM decision have to yield the same solution. Even though DAM involvement can be DAM-scenario specific (DAM decision without information about DAM prices), equal day-ahead market prices provide equal day-ahead transactions indifferent of the subsequent decisions at the third stage are:

$$E^{DAM,\,ch}_{d,h,\omega} = E^{DAM,\,ch}_{d,h,\omega'}, \quad \forall d,h,v,\ \forall \omega,\omega' : \left(\lambda^{DAM}_{d,h,\omega} = \lambda^{DAM}_{d,h,\omega'}\right), \tag{14}$$

$$E^{DAM,\,dch}_{d,h,\omega} = E^{DAM,\,dch}_{d,h,\omega'}, \quad \forall d,h,v,\ \forall \omega,\omega' : \left(\lambda^{DAM}_{d,h,\omega} = \lambda^{DAM}_{d,h,\omega'}\right). \tag{15}$$

Note that the decision variables relating to the Futures Market involvement are declared as node-variable, i.e. without a scenario index, which, contrary to the explicit scenario-variable formulation of the DAM market related decision variables, is why non-anticipativity is implicitly ensured. Decisions related to balancing market transactions are regarded to be wait-and-see decisions, i.e. are taken with full information.

Expected Profit from Balancing Market Transactions

Similarly, the expected profit from balancing market transactions for every period h and every day d is formulated. It is also the scenario probability weighted sum of differences in positive and negative energy deviations, multiplied by the negative and positive balancing market prices over all scenarios:

$$\begin{aligned}
&\mathbb{E}\left\{\Pi^{B}_{\omega}\right\} \\
=\ & \sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H} \pi_\omega \cdot \Pi^{B}_{d,h,\omega} \\
=\ & \sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H} \pi_\omega \cdot \left[\Delta^{+}_{d,h,\omega}\cdot\lambda^{-}_{d,h,\omega} + \Delta^{-}_{d,h.\omega}\cdot\lambda^{+}_{d,h,\omega}\right],
\end{aligned} \tag{16}$$

where both transactions represent a revenue.

Expected Profit from Client Side Transactions

On the client side, the transactions again depend on the real time net buying and selling decision of the markets, which translate into a discharge of the The expected profit is hence the profit formulation for every period h and every day d in a scenario probability weighted sum over all scenarios:

$$\begin{aligned}
&\mathbb{E}\left\{\Pi^{C}_{\omega}\right\} \\
=\ & \sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H} \pi_\omega \cdot \Pi^{C}_{d,h,\omega} \\
=\ & \sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H} \pi_\omega \cdot \left[\sum_{v\in V} E^{RT,\,ch}_{d,v,h,\omega}\cdot\gamma^{ch} - \sum_{v\in V} E^{RT,\,dch}_{d,v,h,\omega}\cdot\gamma^{dch}\right].
\end{aligned} \tag{17}$$

Total Expected Profit for a PEV Aggregator with Multi-Market Involvement

Combining Equations 2, 11, 16 and 17 for the futures procurement cost, as well as expected day-ahead market, balancing market and client side profits, the total expected profit fora PEV aggregator with multi-market involvement is hence:

$$\begin{aligned}
\mathbb{E}\left\{\Pi^{Total}_{\omega}\right\} =\ & -\sum_{d\in D}\sum_{h\in H} C^{F}_{d,h} + \mathbb{E}\left\{\Pi^{DAM}_{\omega}\right\} + \mathbb{E}\left\{\Pi^{B}_{\omega}\right\} + \mathbb{E}\left\{\Pi^{C}_{\omega}\right\} \\
=\ & -\sum_{d\in D}\sum_{h\in H}\sum_{f\in F_{d,h}}\sum_{j\in J}\lambda^{F}_{f,j}\cdot E^{F}_{f,j} + \sum_{\omega\in\Omega}\sum_{d\in D}\sum_{h\in H}\pi_\omega \\
& \cdot\left(\left[\left(E^{DAM,dch}_{d,h,\omega} - E^{DAM,ch}_{d,h,\omega}\right)\cdot\lambda^{DAM}_{d,h,\omega}\right]\right. \\
& + \left[\Delta^{+}_{d,h.\omega}\cdot\lambda^{-}_{d,h,\omega} + \Delta^{-}_{d,h.\omega}\cdot\lambda^{+}_{d,h,\omega}\right] \\
& \left. + \left[\sum_{v\in V} E^{RT,\,ch}_{d,v,h,\omega}\cdot\gamma^{ch} - \sum_{v\in V} E^{RT,\,dch}_{d,v,h,\omega}\cdot\gamma^{dch}\right]\right)
\end{aligned} \tag{18}$$

4.3 Energy Balance

The total expected profit function, expressed in Eq. (18) contains decision variables that need to be constraint according the physical energy exchanged. Two energy balances are formulated, one for the market side and one for the client side.

Similar to Eq. (10), the equality linking the different markets to each other is formulated on an hourly basis to reflect the time granularity of the trading floors:

$$\forall d, h, \omega \; : \tag{19}$$
$$\left(\sum_{v\in V} E^{RT,\,ch}_{d,v,h,\omega} - \sum_{v\in V} E^{RT,\,dch}_{d,v,h,\omega}\right) = \sum_{f\in F_{d,h}} \sum_{j\in J} E^{F}_{f,j} + \left(E^{DAM,\,ch}_{d,h,\omega} - E^{DAM,\,dch}_{d,h,\omega}\right) + \left(\Delta^{+}_{d,h,\omega} - \Delta^{-}_{d,h,\omega}\right),$$

where the real time physical energy exchanged needs to equal the transactions in all three consecutive markets.

On the client side, however, the energy balance is formulated on a vehicle basis:

$$E^{RT,\,dch}_{d,v,h,\omega} + E^{RT,\,ch}_{d,v,h,\omega} \leq av_{d,v,h,\omega} \cdot c_c, \; \forall d, h, \omega, \; \forall v, c : vc_{v,c} = 1, \tag{20}$$

where charging or discharging can only be performed while the vehicles are available. Furthermore, the vehicle specific battery state of charge is expressed by the following inter-temporal energy balance:

$$\forall d, h, \omega, \; \forall v, c : vc_{v,c} = 1 : \tag{21}$$
$$SOC_{d,v,h,\omega} = SOC_{d,v,h-1,\omega} + \left(E^{RT,\,ch}_{d,v,h,\omega} \cdot \eta^{ch}_{c}\right) - \left(\frac{E^{RT,\,ch}_{d,v,h,\omega}}{\eta^{dch}_{c}}\right) - \nabla_{d,v,h,\omega}.$$

Subject to:

$$\forall v, c : vc_{v,c} = 1 :$$
$$SOC_{d,v,h,\omega} \leq bc_c, \; \forall d, h, \omega.$$

In Eq. (21), given an initial level and subject to the available battery capacity constraint, the state-of-charge in one our $SOC_{d,v,h,\omega}$ is equal to the state of charge in the previous hour, plus the inefficient charges $\left(E^{RT,\,ch}_{d,v,h,\omega} \cdot \eta^{ch}_{c}\right)$, less the inefficient discharges $\left(\frac{E^{RT,\,dch}_{d,v,h,\omega}}{\eta^{dch}_{c}}\right)$, and less the reductions due to driving, given by $\nabla_{d,v,h,\omega}$.

The interactions of the PEV aggregator with all the respective trading platforms and on the client interface are once again summarised in Fig. 8 .

4.4 Risk Modeling

To control the volatility of the profit function, i.e. avoiding extremely low profits or high losses, the aggregator could make use of a risk measure. Here, in (22) and (23) the typical conditional value-at-risk (CVaR) formulation with significance level α is used, where the objective function is extended by a weighting factor $\beta \in [0, \infty^{+}]$:

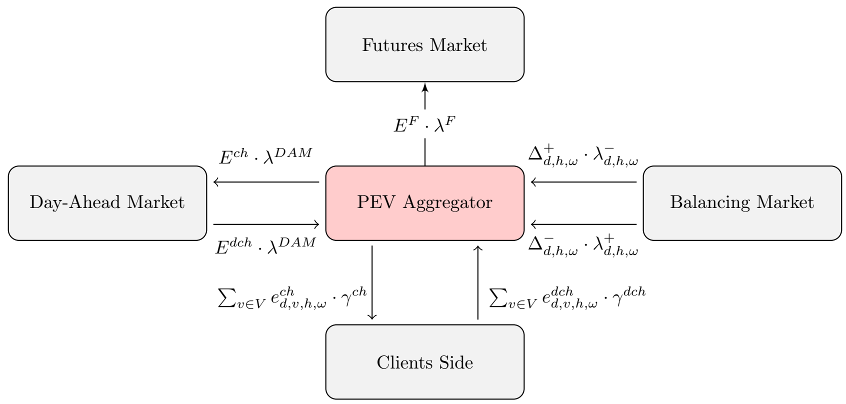


Figure 8: PEV Multi-Market and Client Interactions

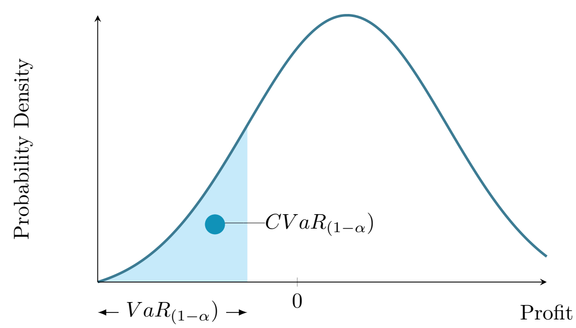


Figure 9: CVaR as a Coherent Risk Measure

$$\text{Maximise}_{\{\imath_\omega,\zeta\}} \quad \beta{\cdot}CVaR = \beta \cdot \left(\zeta - \frac{1}{1-\alpha}\sum_{\omega\in\Omega}\pi_\omega \cdot \imath_\omega\right) \tag{22}$$

Subject to:

$$\begin{aligned} \sum_{d\in D}\sum_{h\in H} C^F_{d,h} &-\Pi^{DAM}_\omega - \Pi^B_\omega - \Pi^C_\omega \\ +\zeta &-\imath_\omega \le 0,\ \forall\omega \\ &\imath_\omega \ge 0,\ \forall\omega. \end{aligned} \tag{23}$$

4.5 Full Formulation

$$\text{Maximise} \quad \left\{E^{F}_{h,f,j}, E^{DAM,dch}_{d,h,\omega}, -E^{DAM,ch}_{d,h,\omega}, \Delta^{+}_{d,h,\omega}, \Delta^{-}_{d,h,\omega}, E^{RT,\,dch}_{d,v,h,\omega}, E^{RT,\,ch}_{d,v,h,\omega}, \imath_\omega, \zeta\right\}$$

$$\mathbb{E}\left\{\Pi^{Total}_{d,h,\omega}\right\} \quad +\beta\cdot CVaR$$

$$= \quad -\sum_{d\in D}\sum_{h\in H} C^{F}_{d,h} + \mathbb{E}\left\{\Pi^{DAM}_{d,h,\omega}\right\} + \mathbb{E}\left\{\Pi^{B}_{d,h,\omega}\right\} + \mathbb{E}\left\{\Pi^{C}_{d,h,\omega}\right\} \quad +\beta\cdot CVaR$$

$$C^{F}_{d,h} = \sum_{f\in F_{d,h}}\sum_{j\in J}\lambda^{F}_{f,j}\cdot E^{F}_{h,f,j}, \ \ \forall d,h$$

$$E^{F}_{h,f,j} \quad \leq \quad \bar{E}^{F}_{f,j}, \ \ \forall f, \forall j$$

$$E^{F}_{f} \quad = \quad \sum_{j\in J} E^{F}_{h,f,j}, \ \ \forall f$$

$$\Pi^{DAM}_{d,h,\omega} = \left(E^{DAM,dch}_{d,h,\omega} - E^{DAM,ch}_{d,h,\omega}\right)\cdot\lambda^{DAM}_{d,h,\omega}$$

$$\Pi^{B}_{d,h,\omega} = \Delta^{+}_{d,h.\omega}\cdot\lambda^{-}_{d,h,\omega} + \Delta^{-}_{d,h.\omega}\cdot\lambda^{+}_{d,h,\omega}$$

$$\Pi^{C}_{d,h,\omega} = \sum_{v\in V} E^{RT,\,ch}_{d,v,h,\omega}\cdot\gamma^{ch} - \sum_{v\in V} E^{RT,\,dch}_{d,v,h,\omega}\cdot\gamma^{dch}$$

$$\forall d,h,\omega \ :$$

$$\left(\sum_{v} E^{RT,\,ch}_{d,v,h,\omega} - \sum_{v} E^{RT,\,dch}_{d,v,h,\omega}\right) \quad = \quad \sum_{f\in F_{d,h}}\sum_{j\in J} E^{F}_{h,f,j} + \left(E^{DAM,\,ch}_{d,h,\omega} - E^{DAM,\,dch}_{d,h,\omega}\right) + \left(\Delta^{+}_{d,h,\omega} - \Delta^{-}_{d,h,\omega}\right)$$

$$E^{RT,\,dch}_{d,v,h,\omega} + \quad E^{RT,\,ch}_{d,v,h,\omega} \quad \leq av_{d,v,h,\omega}\cdot c_c, \ \forall d,h,\omega, \ \forall v,c : vc_{v,c} = 1$$

$$SOC_{d,v,h,\omega} \quad = SOC_{d,v,h-1,\omega} \quad + \left(E^{RT,\,ch}_{d,v,h,\omega}\cdot\eta^{ch}_{c}\right) - \left(\frac{E^{RT,\,dch}_{d,v,h,\omega}}{\eta^{dch}_{c}}\right) - \nabla_{d,v,h,\omega}, \ \forall d,h,\omega, \ \forall v,c : vc_{v,c} = 1$$

$$SOC_{d,v,h,\omega} \quad \leq bc_c, \ \forall d,h,\omega, \ \forall v,c : vc_{v,c} = 1$$

$$E^{DAM,\,dch}_{d,t,\omega} \quad \leq E^{DAM,\,dch}_{d,t,\omega'}, \quad \forall d,h, \ \forall \omega,\omega' : \ O\left(\lambda^{DAM}_{d,t,\omega}\right) + 1 = O\left(\lambda^{DAM}_{d,t,\omega'}\right)$$

$$E^{DAM,\,ch}_{d,t,\omega'} \quad \leq E^{DAM,\,ch}_{d,t,\omega}, \quad \forall d,h, \ \forall \omega,\omega' : \ O\left(\lambda^{DAM}_{d,t,\omega}\right) + 1 = O\left(\lambda^{DAM}_{d,t,\omega'}\right)$$

$$E^{DAM,\,ch}_{d,t,\omega} \quad = E^{DAM,\,ch}_{d,t,\omega'}, \quad \forall d,h, \ \forall \omega,\omega' : \ \lambda^{DAM}_{d,t,\omega} = \lambda^{DAM}_{d,t,\omega'}$$

$$E^{DAM,\,dch}_{d,t,\omega} \quad = E^{DAM,\,dch}_{d,t,\omega'}, \quad \forall d,h, \ \forall \omega,\omega' : \ \lambda^{DAM}_{d,t,\omega} = \lambda^{DAM}_{d,t,\omega'}$$

$$CVaR = \left(\zeta - \frac{1}{1-\alpha} \sum_{\omega \in \Omega} \pi_\omega \cdot \imath_\omega \right)$$

$$\begin{aligned} \sum_{d \in D} \sum_{h \in H} C^F_{d,h} + \zeta \quad -\Pi^{DAM}_\omega - \Pi^B_\omega - \Pi^C_\omega - \imath_\omega \quad &\leq 0,\ \forall \omega \\ \imath_\omega \quad &\geq 0,\ \forall \omega. \end{aligned}$$

5 Preliminary Stylized Example

In order to test the above presented model capability, preliminarily, a stylized example could be studied as follows.

5.1 Description

Three runs:

1. Stochastic Load:
   - No control over vehicles.
   - $E^{DAM,\,dch}_{d,t,\omega'} = \nabla_{d,h,\omega}$: constraint 20 is relaxed
   - Markets: Access to Futures and DAM but no Balancing
2. Real-time trading with direct load control (DLC):
   - Control over vehicles
   - Markets: Trading in a) Balancing or b) Day-Ahead Market only
3. Full Model:
   - DLC
   - All markets

- ⇒Value of control and flexibility

5.2 Input

The market horizon only spans the 24 hours of the first day of the week, i.e. $Monday$, hence the subscript d can be omitted for this example case. In the following the input data defining the example case in terms of Futures Contracting Data, Day-Ahead Market Price Scenarios, Balancing Market Price Scenarios, and the Mobility and Fleet Unavailability Scenarios, is presented. Finally the resulting scenario tree is illustrated.

Futures Contracting Data

The futures contracting data of this stylized example consists of three possible futures contracts, each spanning over the entire market horizon of 24h and having three equally sized blocks with a maximal contracting quantitiy of 100 [kWh].

Table 2: PEV Aggregator Example: Futures Contracting Curve Data

Contract # f	Duration	$\lambda^F_{f\,1}$	$\lambda^F_{f\,2}$	$\lambda^F_{f\,3}$	$E^F_{f,1}$	$E^F_{f,2}$	$E^F_{f,3}$
		[€/MWh]			[kWh]		
1	24h	70	80	90	30	30	30
2	24h	75	80	85	30	30	30
3	24h	71	73	75	30	30	30

Table 3: PEV Aggregator Example: Day-Ahead Market Scenario Price Data

Sub-Scenario # ω	Probability π_ω	$\mathbb{E}\left\{\lambda^{DAM}\right\}$ [€/MWh]
DAM1	0.2	45
DAM2	0.4	55
DAM3	0.4	65

Day-Ahead Market Price Scenarios

The day-ahead market price scenarios, constituted by vectors of 24 hourly price elements are only indicated by means of the average price $\mathbb{E}\left\{\lambda^{DAM}\right\}$, as depicted in 10, all following the same typical diurnal price profile with high maximum price of $\mathbb{E}\left\{\lambda^{DAM}\right\} + 20\%$ €/MWh occurring at night (19h), low minimum price of $\mathbb{E}\left\{\lambda^{DAM}\right\} - 30\%$ €/MWh occurring during the early morning hours (3h).

Client Side Prices

The client side price parameters, which are also indicatd in 10, are 70 and 90 €/MWh for γ^{ch} and γ^{dch}, respectively.

Balancing Market Price Scenarios

Suppose for simplicity that the balancing market outcome vectors of the considered day d, ϱ^+_h and ϱ^-_h, can for all hours h be conveniently reduced to one scalar each for positive and negative

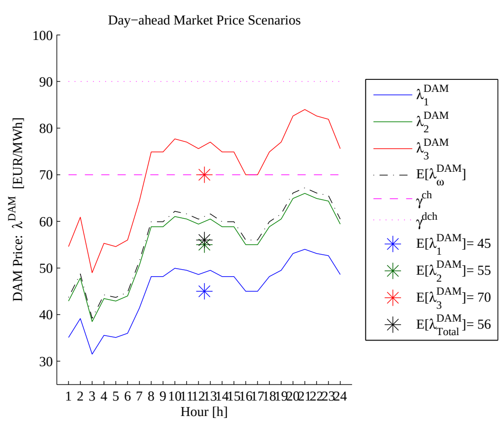


Figure 10: PEV Aggregator Example: Day-Ahead Market Scenario Price Profiles

Table 4: PEV Aggregator Example: Balancing Market Price Scenarios

Sub-Scenario # ω	Probability π_ω	ϱ^+	ϱ^-
B1	0.6	1	1.5
B2	0.4	0.9	1

Table 5: PEV Aggregator Example: Fleet Characteristics [9],[12]

Parameter	PHEV $c = 1$	BEV $c = 2$
Available Battery Capacity bc_c [kWh]	10	20
Connection Capacity c_c [kW]	3.6	3.6
Driving Speed ϑ_c [km/h]	30	30
Driving efficiency η_c^{drive} [kWh/km]	0.14	0.16
Charging efficiency η_c^{charge} [p.u.]	0.93	0.93

deviation as depicted in 4. That is, equally for each hourly day-ahead market price, the system has a probability ($\pi_{B1} = 0.6$) to deviate positively and one to deviate negatively ($\pi_{B2} = 0.4$).

Mobility / Fleet Unavailability Scenarios

Suppose a small fleet of 5 vehicles, which are made up of 100% Plug-in Hybrid Electric Vehicles (PHEVs) and 0% full Battery Electric Vehicles (BEVs), whose characteristics are shown in 5 based on [?] and [?]. The unavailability is depicted in the graphical visualizations of $av_{Monday,v,h,\omega}$ and $\nabla_{Monday,v,h,\omega}$. Initial SOCs are, in both mobility sub-scenarios at 0.7 and 0.6 for classes 1 and 2 respectively. Mobility sub-scenarios 1 and 2 are equiprobable and hence occur both with a chance of 50%. In order to obtain the mobility scenarios the mobility scenario generation algorithm (detailed in the appendix) is executed to generate 100 scenarios. To find the extreme cases, those scenarios yielding the maximum and minimum values for variances (along the time dimension across 24h) in cumulated SOC reduction.

Scenario Tree for Stylized Example

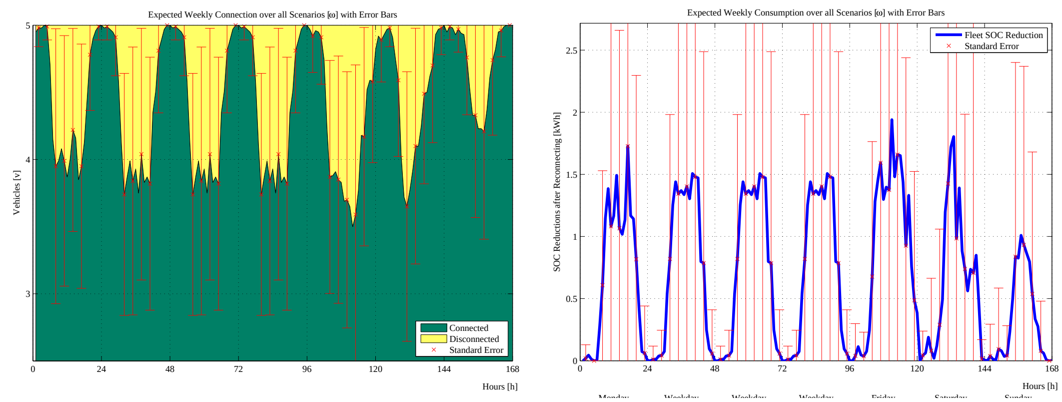
In Fig. 14 an overview of the sub-scenario to full scenario composition with according probabilities is given.

Different Scenario Trees are Tested

Depending on the assumptions about what knowledge is available at what decision stage different scenario trees can be constructed. Besides the known base case with full price information at market involvement shwon in 15a, two variants are introduced. Fig. 15b shows an illustration of the scenario tree with DAM offer curve constraints and Fig. 15c shows an illustration of the scenario tree with DAM offer curve constraints as well as non-anticipativity of Balancing Prices even though information about mobility is available the decision of balancing market involvement.

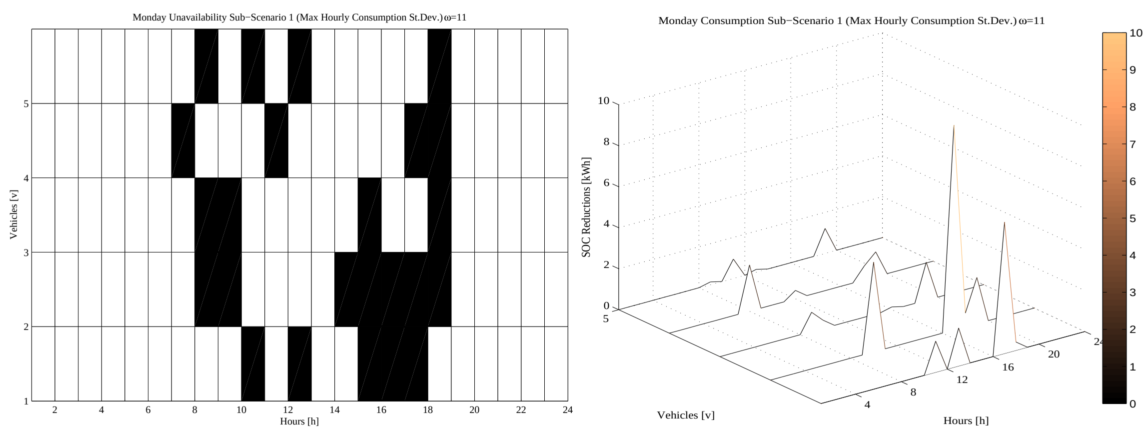
5.3 Expectation - Hypothesis Formulation

- Futures Data
  - calibrated to show the effect of adding certainty when increasing value at risk weights. The more risk averse the aggregator the more futures contracts are included in the procurement portfolio. Even though the prices are higher and therefore expected profits are lower, the decrease in profit variance is appreciated.



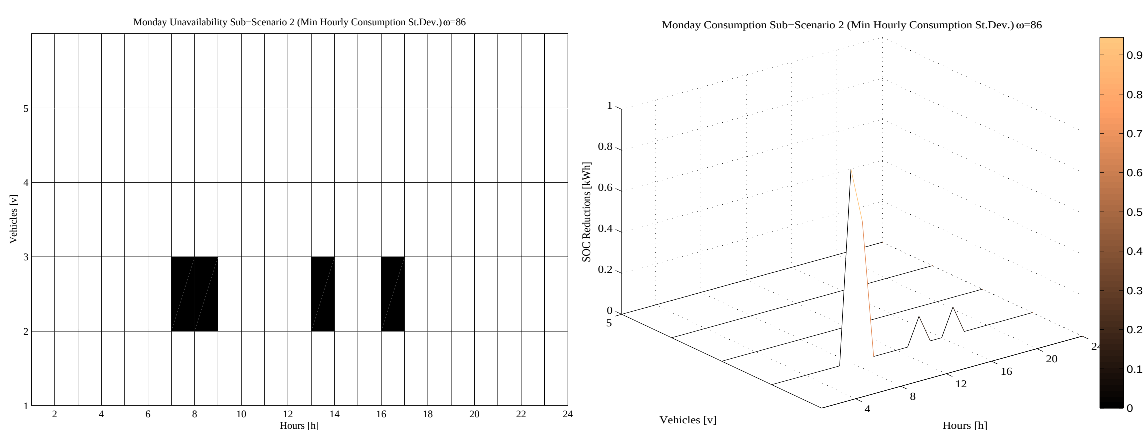
(a) SOC Reductions (b) Cumulated Availabilty

Figure 11: Fleet Mobility



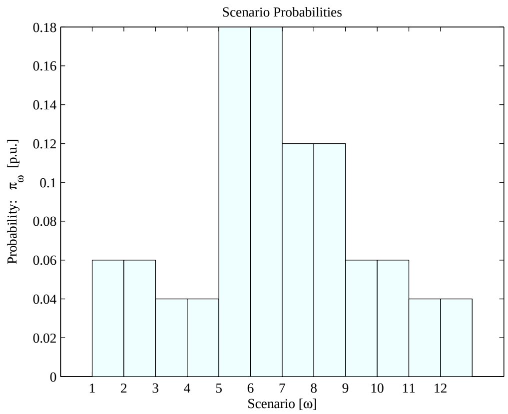
(a) Unavailability $av_{Monday,v,h}$ (b) State-of-Charge Reductions $\nabla_{Monday,v,h}$

Figure 12: Mobility Sub-Scenario M1



(a) Unavailability $av_{Monday,v,h}$ (b) State-of-Charge Reductions $\nabla_{Monday,v,h}$

Figure 13: Mobility Sub-Scenario M2



ω	π_ω	Day-Ahead	Balancing	Mobility
1	0.06	DAM1	B1	M1
2	0.06	DAM1	B1	M2
3	0.04	DAM1	B2	M1
4	0.04	DAM1	B2	M2
5	0.18	DAM2	B1	M1
6	0.18	DAM2	B1	M2
7	0.12	DAM2	B2	M1
8	0.12	DAM2	B2	M2
9	0.06	DAM3	B1	M1
10	0.06	DAM3	B1	M2
11	0.04	DAM3	B2	M1
12	0.04	DAM3	B2	M2

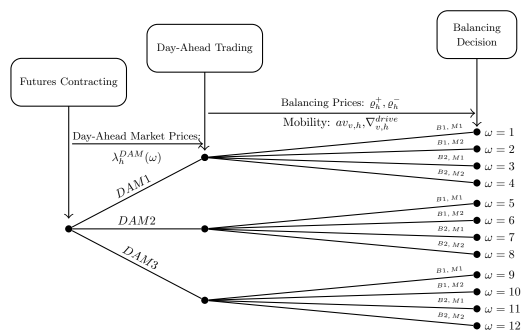
Figure 14: Scenario Probabilities

- are in the range between resale energy price γ^{ch} and energy compensation price γ^{dch}, and above the expected energy price of 57 €/MWh – this means in the futures market, energy can be bought at prices that on the whole should not justify reselling of energy bought from futures (too expensive)
- on the contrary it can be expected to see a lot of buying (probably up to the upper limit) prices might need to be calibrated to show efficient frontier
- energy quantities need to be constraint at right sizes corresponding to total demand, constraining net energy exchange

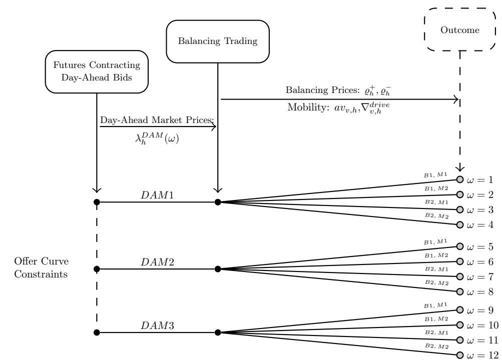
- DAM data
  - expected prices per scenario: [45.54,55.66,70.66] and overall: 57
  - three price scenarios including significant spreads between diurnal min and max, also with higher probs for the high price scenarios
  - ceterus paribus: one would expect to see aggregated charging at early morning and discharging at early evening
- Balancing data
  - severe impact if 1.5 upward change → expectation of upward dominating effect overriding others. definitely test by isolating
- Mobility
  - total demand per scenario: [35.84   1.89] kWh
  - in the ubiquitous charging infrastructure case little impact of unavailability. In the charge after last trip case bigger impact and more aligned with MID prefiltering criteria of (Stellplatz vorhanden)

5.4 Output/Discussion

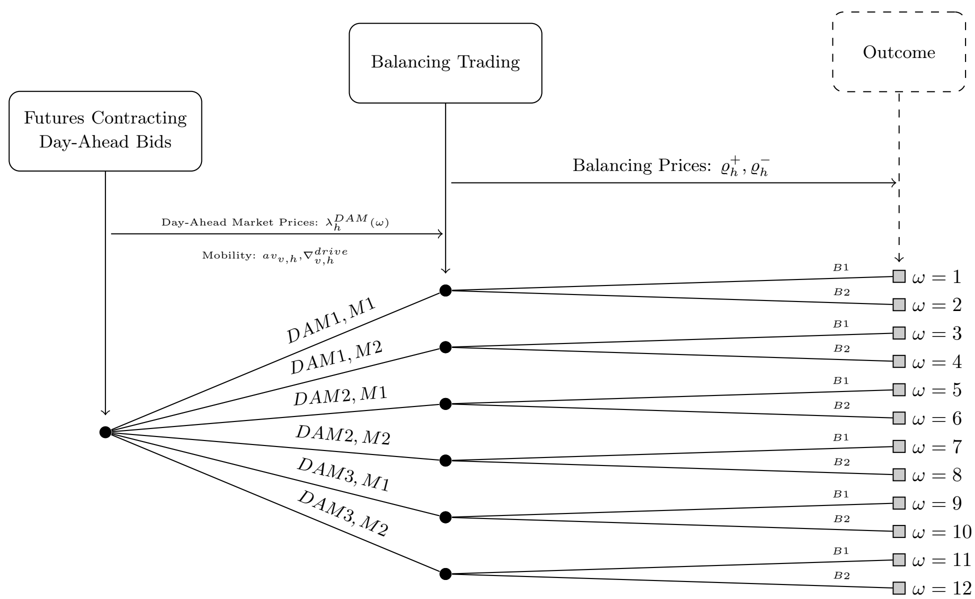
The following analyses and interprets basic model results from the example case.



(a) Scenario Tree First Day of Week: PEV Aggregator in Sequential Markets



(b) Variant 2: With DAM Offer Curve Constraints



(c) Variant 3: With DAM Offer Curve Constraints and Information about Mobility at Balancing Decision

Figure 15: Scenario Tree Variants

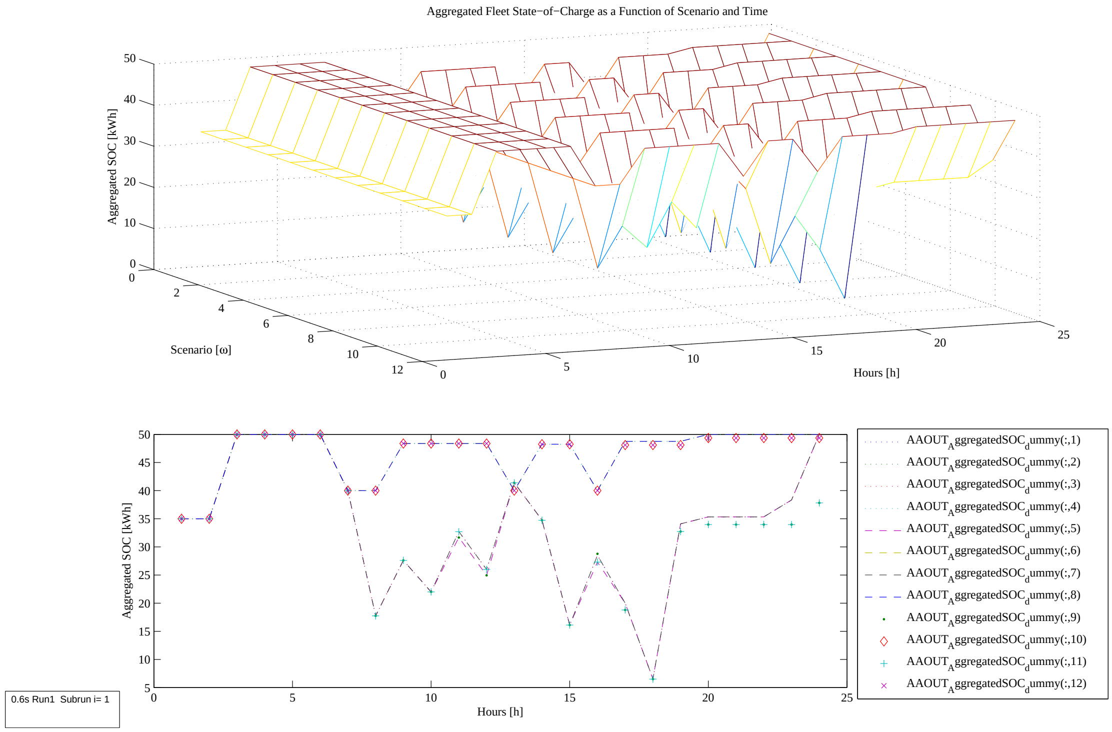


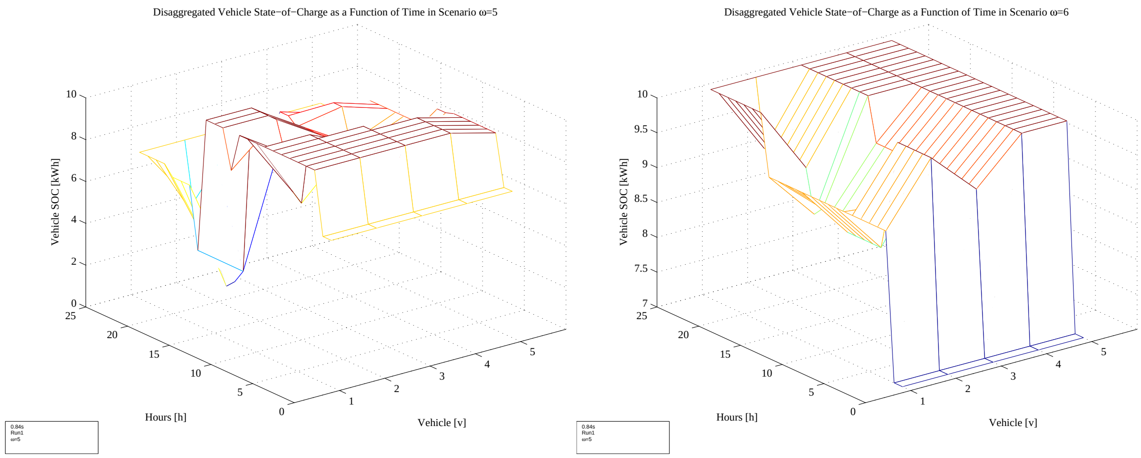
Figure 16: Illustration of Aggregated SOCs

Aggregated SOC of the Entire PEV Fleet

The expectations are met: aggregated charging appears at early morning and discharging at early evening. However, the original presumption of no variations over of aggregated charging in different scenarios with the same mobility profile does not hold in all its detail. In general the basic tendencies are observed: With increasing scenario counts (higher DAM prices) the final SOC is closer to its minimum requirement of 70%:$\uparrow \omega, \uparrow \lambda \Longrightarrow \sum_v SOC_{v,24,\omega} \rightarrow SOC_{min} = 0.7 \cdot |V| \cdot bc_c$. Vice versa with decreasing scenario counts (lower DAM prices) the final SOC is closer to its maximum battery capacity: $\downarrow \omega, \downarrow \lambda \Longrightarrow \sum_v SOC_{v,24,\omega} \rightarrow SOC_{max} = |V| \cdot bc_c$. However the mobility seems to override this effect such that alternating scenarios are close to or at either one of the extremes. In the low mobility scenarios (even scenario counter) the high availability permits charging at earlier time steps, while in the high mobility scenarios (uneven scenario counter) the low availability commands for late a lot of afternoon, little evening and then a lot of late night charging. Everything in accordance with the price profiles. A detailed graphical illustration can be studied in Fig. 16.

Disaggregated SOCs of Individual PEVs in selected Scenarios

Two selected scenarios $\omega = 5$ and $\omega' = 6$ who exhibit different cases of mobility, the former with high and the latter with low unavailability, are compared to each other in terms of PEV SOCs on an individual basis. Results comply with the intuitive expectation and the analysis of aggregated SOCs. It can be observed that in the scenario of high unavailability, $\omega = 5$, all vehicles are first charged to be prepared for the subsequent SOC reductions due to driving. Charging is then accorded with the market prices in the evening and late night. In the scenario pertaining to low unavailability, $\omega' = 6$, all vehicles are charged in the first hours of the day, only vehicle 2 is being discharged due to its driving and shortly thereafter replenished. The two sub-figures of Fig. 17 give rise to further insights.



(a) Scenario $\omega = 5$ (b) Scenario $\omega' = 6$

Figure 17: Disaggregated SOCs of Individual PEVs

Scenario Profit Calculations

Fig. 18 provides a graphical visualisation of the different profits in all the scenarios. It can be observed that Π_ω^C the profit on the client side, i.e. on the retail market, mainly depends on the mobility scenario. In high mobility scenarios the profit increases because the sales volume increases and in low mobility scenarios vice versa. According with the SOC analysis from above, scenarios $\omega = 9$ and $\omega = 11$ DAM prices are so unfavouribly high that the sales volume decreases as well. The mean value of retail client profit is $\mathbb{E}\left\{\Pi_\omega^C\right\} = 2.45$. On the cost side, i.e. procurement from DAM Π_ω^{DAM} and futures markets C_f , the same alternation of high and low mobility scenarios and according sales volumes can be seen. The cost of the futures purchases is constant $C_f = -0.09$ for all scenarios, because as a first stage here-and-now decision it is not scenario dependent. Finally the total profit Π_ω^{Total}, as a sum of the formerly mentioned, is decreasing with the higher scenario counts. Its expected value remains slightly positive at $\mathbb{E}\left\{\Pi_\omega^{Total}\right\} = 0.69$.

Day-Ahead Market Involvement

The resulting day-ahead market involvement of the PEV-Aggregator can be assessed in Fig. 19. Sub-figure a) shows the charging and sub-figure b) shows the discharging (which is currently fixed to 0). The relaxed the non-anticipativity constraints as well as increasing-DAM-bid-curve constraints lead to the nature of the decision variable $E_{h,\omega}^{DAM,ch}$. The bids have to be the same for the batches of scenarios $\omega = \{1, 2, 3, 4\}$, $\omega = \{5, 6, 7, 8\}$ and $\omega = \{9, 10, 11, 12\}$, because they respectively yield the same DAM prices: $\lambda_{h,w}^{DAM}$.

When introducing imbalances:

In general it is important to remember that the ESS can perform two services: inter-temporal energy arbitrage within either the day ahead, or within the balancing market as well as inter-market transactions, here in the form of balancing energy to other participants. The second service is described in further detail in the following: When a system imbalance $\delta \neq 0$ occurs, two situations

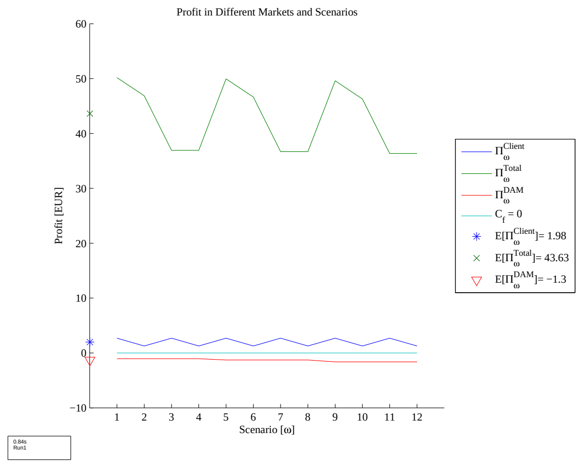
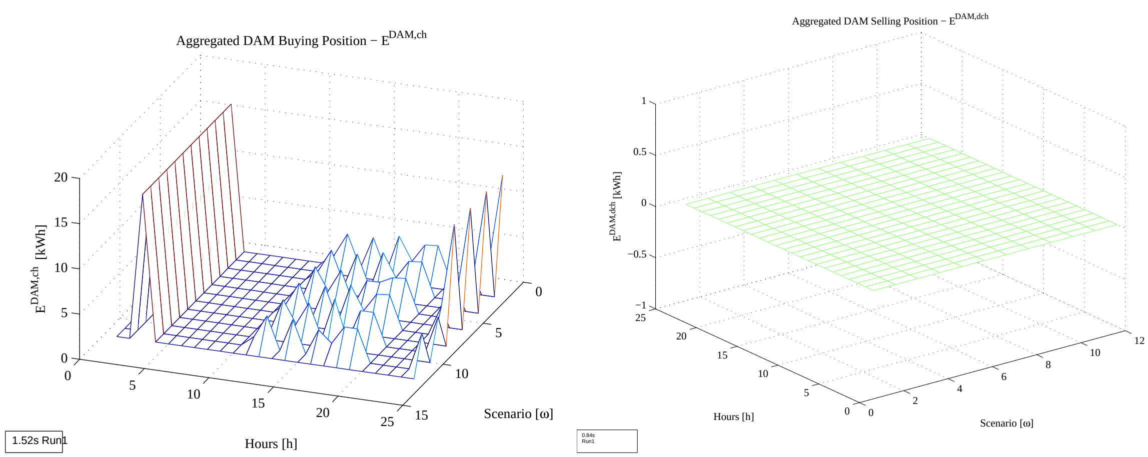


Figure 18: Scenario Profits



(a) Charging – Buying Positions

(b) Discharging – Selling Positions

Figure 19: Day-Ahead Market Involvement

are imaginable. Either the electric power system experiences a *positive* deviation, $\delta > 0$, (from the demand side) or a *negative* one, $\delta < 0$.

In case of a *positive* deviation at real time physical delivery there is an excess demand in the system with respect to a previous market clearing. This results in a positive balancing market price higher or equal to the DAM, $\lambda_h^+ \geq \lambda_h^{DAM}$, while the negative balancing market price remains at DAM level $\lambda_h^- = \lambda_h^{DAM}$. For a consumer/retailer representing a net demand with a buying position, this means that an under-consumption compared to the DAM clearing Δ_h^-would be remunerated with λ_h^+, compared to trading the same energy in the DAM leading to a decreased procurement cost of $\Delta_h^- \cdot \left(\lambda_h^+ - \lambda_h^{DAM}\right) = \Delta_h^- \cdot \left(\varrho_h^+ - 1\right)$, which is positive for large enough system imbalances. An over-consumption, on the other hand, would result in a penalisation of the magnitude $\Delta_h^+ \cdot \left(\lambda_h^- - \lambda_h^{DAM}\right) = \Delta_h^- \cdot \left(\varrho_h^+ - 1\right) \overset{\delta>0}{=} \Delta_h^- \cdot (1-1) = 0$, as opposed to procuring the same energy in the day-ahead market. Evidently, these situations are mutually exclusive.

Accordingly, in case of a *negative* system deviation at real time physical delivery and a lack of demand occuring with respect to the DAM clearing, $\delta < 0$, resulting in a positive balancing market price equal to the DAM, $\lambda_h^+ = \lambda_h^{DAM}$, and the negative balancing market price greater or equal to DAM level $\lambda_h^- \geq \lambda_h^{DAM}$. In this case, the market agents also have two options. They can either favour the system by deviating with opposite sign and be remunerated with $\Delta_h^+ \cdot \lambda_h^-$, i.e. consuming more than scheduled in DAM and, as a consumer, having an a decreased procurement cost of $\Delta_h^+ \cdot \left(\lambda_h^- - \lambda_h^{DAM}\right) = \Delta_h^+ \cdot \left(\varrho_h^- - 1\right)$, which is positive for large enough system imbalances. Or, they can consume less, which would result in a penalisation of the magnitude $\Delta_h^- \cdot \left(\lambda_h^+ - \lambda_h^{DAM}\right) = \Delta_h^- \cdot \left(\varrho_h^+ - 1\right) \overset{\delta<0}{=} \Delta_h^- \cdot (1-1) = 0$, as opposed to procuring the same energy in the day-ahead market.

Moreover:

- All runs performed on Windows XP Machine Intel©Core™i7 CPU 860 at 2.8 GHz, 3.34 GB RAM with MatLab(2011b)-GAMS(23.8)-Hybrid and CPLEX solver.
- Solving time of LP: around 3-8s per iteration for runs of type 2 b) with 27k rows and 40k columns

Potential output calculations could include:

- Expected profit
- Profit standard deviation
- CVaR vs. Expected Profit
- Expected generation and sales
  - expected DAM generation/consumption (over different runs)
  - Expected BM generation/consumption
- Adjusted pdfs of the profit for arrays of betas
- VSS and EVPI?
- Certainty gain effect?

6 Case Study

Same as stylized example but scenarios to full extent.

7 Preliminary Conclusions, A Tentative Summary

1. Detailed formulation of the self scheduling of a PEV aggregator taking into account uncertainty about prices and mobility.
2. Aggregated Vehicle Batteries are likely to present a physical hedge against market price risk .
3. The flexibility of the storage may – even though subject to conservative capacity connection constraints – be compared to the risk of unavailability.
4. Balancing markets may provide an augmented opportunity for low risk profit.

Main Assumptions

Limitations of the Approach:

1. Two state mobility world:
   (a) Ubiquitous Charging Infrastructure [could be relaxed saying vehicles are only available after last trip of the day, assuming that journey's mobility always finishes at a charging outlet under the aggregator's control]
   (b) Mobility is most likely not equal to actual connection behaviour
2. Communication and Control
   (a) Real time load control
   (b) Roaming model: vehicles have ID and access to all charging points
3. Statistical independence of the stochastic mobility processes
4. Perfect information about the balancing prices at real time
5. Market assumptions:
   (a) DAM price in EEX always positive
   (b) Futures contracts in EEX on a monthly basis

Future Work

- Include selling/buying price decision and according elasticity of the demand (as a function of the vehicle fleet size)
- Full size realistic case study:
  - Acquiring market data for futures, day-ahead and balancing market prices
  - Fitting SARIMA models for prices and scenario generation
  - Mobility scenario generation (improvements and alternative approaches: e.g. [18], [12])
  - Scenario Reduction for exogenous uncertainty with SCENRED [15]
- Include capacity degradation of PEV batteries
- Introduce locational pricing in the form of demand rate type use-of-system charges based on spare capacity
- Using options for hedging against idiosyncratic risk [17]

Acknowledgement

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Many thanks are directed at the supervisors from the REDES group, notably Pablo Frías and other helpful consultants, above all, Michel Rivier and Germán Morales.

Appendix

Supplemental Notation for Mobility Scenario Generation Algorithm

$t \in T$ Index of trips on a given day d.

Input

π_d^{travel} The probability of travel on a certain day d, $\in [0, 1]$.

$\pi_{d,h}^{startH}$ The probability of starting a trip on a specific day d and hour h, $\in [0, 1]$.

$\pi_{d,l}^{range}$ The probability of a trip to be of a certain length l on a specific day d, $\in [0, 1]$.

ntr_d^{avg} The expected number of trips for each of the moving vehicles on a given day, $\in \mathbb{R}^+$.

Output

$trv_{d,v}$ Binary matrix indicating availability of a vehicle v on a certain day d, $\in \{0; 1\}$.

$shr_{d,v,t}$ Integer matrix indicating the starting hour of a trip t by vehicle v on a certain day d, $\in H$.

$rhr_{d,v,t}$ Integer matrix indicating the return hour of a trip t by vehicle v on a certain day d, $\in H$.

$lgt_{d,v,t}$ Positive real matrix indicating the length of a trip t by vehicle v on a certain day d, $\in \mathbb{R}^+$.

Algorithm for Mobility Scenario Generation

An overview of the algorithm is provided in form of a flow chart in20 and an indication of time performance given in 21. The total number of scenarios characterizing the scenario tree for any trip of one vehicle on a given day is hence $N_\Omega^{startH} \times N_\Omega^{range} = 24 \times 21 = 501$. However, since vehicles are likely to do more than one trip per day, each availability/mobility scenarios is generated following the subsequent algorithm.

- Let $trv_{d,v}$ be a binary matrix with the dimensions $|d| \times N_v$
  - For each element of $trv_{d,v}$ independently draw a realization of $\lambda^{start} = \lambda^{start}(\omega)$ and assign a binary value indicating whether vehicle v leaves on the respective day d. A vehicle, which does not leave results in availability in terms of system connection, hence the coding is 1 for availability and 0 for non availability.
  - Let $shr_{d,v,t}$ be an integer matrix with the dimensions $|d| \times N_v \times max_d \lceil ntr_d^{avg} \rceil$
    - For each element of $shr_{d,v,t}$ independently draw a realization of $\lambda^{startH} = \lambda^{startH}(\omega)$ and assign the trip's starting hour to the respective element, if and only if the vehicle is travelling on the respective day
  - Let $lgt_{d,v,t}$ be an integer matrix with the dimensions $|d| \times N_v \times max_d \lceil ntr_d^{avg} \rceil$
    - For each element of $lgt_{d,v,t}$ independently draw a realization of $\lambda^{range} = \lambda^{range}(\omega)$ and assign the trip length to the respective element, if and only if the vehicle is travelling on the respective day
  - Plausibility checks have to be performed for each day's mobility as follows:
    - For each d and each v :

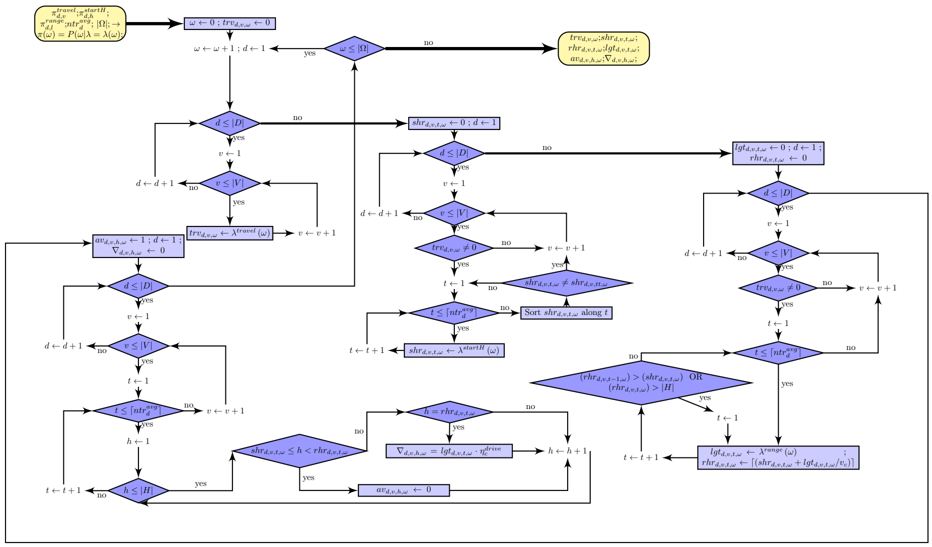

Figure 20: Flow Chart of Mobility Scenario Generation Algorithm

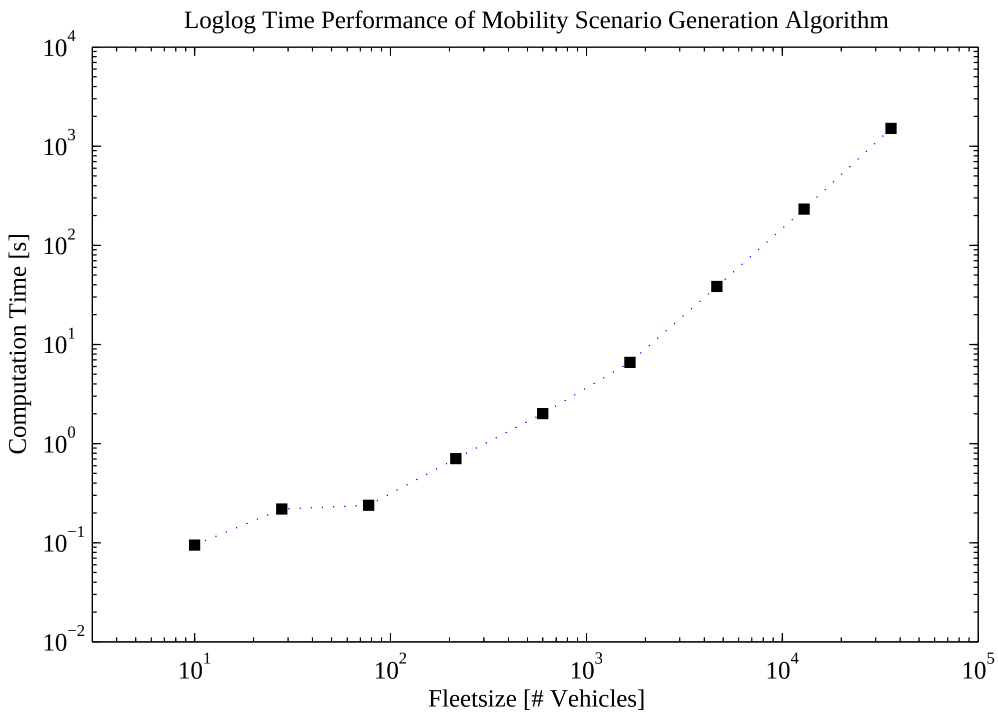

Figure 21: Time Performance of Mobility Scenario Generation Algorithm: Computation Time vs. Fleet Size

Table 6: Expected Trips of Moving Vehicles [3, 10, 11]

	Monday	Weekday	Friday	Saturday	Sunday
ntr_d^{avg}	3.95044	3.96463	4.21066	3.59744	2.8098

Table 7: Travel Probability π_d^{travel} [3, 10, 11]

π_d^{travel}	Monday	Weekday	Friday	Saturday	Sunday
Travel	0.6273	0.6586	0.6494	0.5499	0.4066
No Travel	0.3727	0.3414	0.3506	0.4501	0.5934

- · sort the random start times of the trips of a vehicle on a certain day in ascending order.
- · For for each t from 0 to $\lceil ntr_d^{avg} \rceil$:
- · increase trip counter $t \leftarrow t + 1$
- · in case $t < \lceil ntr_d^{avg} \rceil$:
- · while $shr_{d,v,t}+lgt_{d,v,t}/\vartheta > shr_{d,v,t+1}$ redraw independent realizations of $\lambda^{range} = \lambda^{range}(\omega)$ for $lgt_{d,v,t}$
- · and in case$t = ntr_d^{avg} \rceil$:
- · while $shr_{d,v,t} + \{ntr_d^{avg}\} \cdot lgt_{d,v,t}/\vartheta_c > N_h$ redraw independent realizations of $\lambda^{range} = \lambda^{range}(\omega)$ for $lgt_{d,v,t}$, where $\{ntr_d^{avg}\}$ denotes the fractional part of the last trip defined by the formula $\{ntr_d^{avg}\} := ntr_d^{avg} - \lfloor ntr_d^{avg} \rfloor$ and $\lfloor \cdot \rfloor$ ($\lceil \cdot \rceil$) denotes the floor (ceiling) function mapping ntr_d^{avg} to the largest(smallest) integer smaller (larger) than ntr_d^{avg}. Hence, $0 < \{\cdot\} < 1$.
- · The second while-loop assures the returns before the end of the day. Hence, for simplification the number of cars disconnected at the beginning of a diurnal 24-hour period (midnight of the previous day) is always equal to the number of cars disconnected at the end of it (midnight of current day)

– Evaluate $rhr_{d,v,t} = shr_{d,v,t} + lgt_{d,v,t}/\vartheta_c$ element-wise for obtaining return times, which results in $rhr_{d,v,t} > shr_{d,v,t}, \ \forall d, v, h$.

– Let $av_{d,v,h}$ be a binary matrix of dimensions $N_d \times N_v \times N_h$ indicating the availability of a vehicle in a certain hour and initialize as available: $av_{d,v,h} = 1, \ \forall d, v, h$.

  ∗ For each d and each v and t from 1 to $\lceil ntr_d^{avg} \rceil$ and each h:

    · if $h \geqq shr_{d,v,t} \ \wedge \ h < rhr_{d,v,t}$: set $av_{d,v,h} = 0$

As stated in the introduction the mobility of the PEV fleet does not only determine the unavailability to the system, it also characterizes the electricity demand of each vehicle. From the above information given by the realizations of the stochastic processes it is possible to derive the energy demand:

- For a given trip of distance $lgt_{d,v,t}$ performed by a type of car c the trip's electricity consumption while driving, and constituting the reduction in state-of-charge (SOC) of the at reconnecting hour $rhr_{d,v,t}$ reconnecting battery is calculated for each d and each v and t from 1 to $\lceil ntr_d^{avg} \rceil$ and each h:

  – if $h = rhr_{d,v,t}$: set $\nabla_{d,v,h}^{drive} = lgt_{d,v,t} \cdot \left(\eta_c^{drive}/\eta_c^{charge}\right)$, where $\nabla_{d,v,h}^{drive}$ indicates the SOC loss due to the previous trip's driving

Table 8: Trip Start Hour Probability $\pi_{d,t}^{startH}$ [3, 10, 11]

Hour h	Monday	Weekday	Friday	Saturday	Sunday
1	1.212E-03	1.893E-03	4.088E-03	6.031E-03	2.429E-03
2	1.943E-04	1.192E-03	3.262E-03	2.838E-03	1.242E-03
3	1.170E-03	6.696E-04	1.499E-03	2.889E-03	1.277E-03
4	7.647E-04	1.353E-03	2.873E-03	1.976E-03	4.130E-03
5	3.080E-03	5.862E-03	5.984E-03	1.384E-03	2.979E-03
6	1.815E-02	2.242E-02	1.717E-02	5.854E-03	5.785E-03
7	4.940E-02	5.141E-02	4.212E-02	1.305E-02	6.236E-03
8	7.007E-02	7.309E-02	6.572E-02	2.744E-02	1.827E-02
9	6.028E-02	5.966E-02	6.199E-02	6.892E-02	4.338E-02
10	6.578E-02	5.658E-02	6.035E-02	1.143E-01	6.801E-02
11	6.034E-02	5.627E-02	6.190E-02	1.199E-01	6.865E-02
12	5.684E-02	6.026E-02	5.716E-02	1.029E-01	8.973E-02
13	6.083E-02	6.525E-02	6.572E-02	9.099E-02	7.824E-02
14	5.863E-02	5.981E-02	6.860E-02	7.072E-02	8.667E-02
15	5.943E-02	6.264E-02	7.702E-02	6.825E-02	9.260E-02
16	7.976E-02	7.260E-02	8.355E-02	6.136E-02	7.352E-02
17	8.835E-02	9.267E-02	8.378E-02	4.296E-02	7.509E-02
18	8.757E-02	8.735E-02	7.397E-02	4.405E-02	7.987E-02
19	6.572E-02	6.392E-02	5.592E-02	4.967E-02	7.215E-02
20	4.480E-02	4.105E-02	4.199E-02	4.056E-02	4.310E-02
21	2.593E-02	2.561E-02	2.393E-02	2.076E-02	3.257E-02
22	2.365E-02	1.963E-02	1.802E-02	1.402E-02	2.713E-02
23	1.339E-02	1.379E-02	1.568E-02	1.801E-02	2.092E-02
24	4.665E-03	5.006E-03	7.723E-03	1.118E-02	6.036E-03

Table 9: Trip Range Probability $\pi_{d,l}^{range}$ [3, 10, 11]

Trip Length l	Monday	Weekday	Friday	Saturday	Sunday
1	2.292E-01	2.111E-01	2.246E-01	2.111E-01	2.002E-01
3	1.780E-01	1.783E-01	1.671E-01	1.783E-01	1.594E-01
5	9.996E-02	1.214E-01	1.175E-01	1.214E-01	1.187E-01
7	9.172E-02	8.147E-02	9.230E-02	8.147E-02	7.652E-02
9	5.679E-02	6.149E-02	6.245E-02	6.149E-02	5.714E-02
11.25	3.471E-02	4.829E-02	4.989E-02	4.829E-02	5.119E-02
13.75	6.441E-02	6.157E-02	4.999E-02	6.157E-02	6.202E-02
16.75	4.989E-02	3.950E-02	4.922E-02	3.950E-02	4.632E-02
19.25	3.439E-02	3.239E-02	3.018E-02	3.239E-02	4.356E-02
22.5	4.960E-02	5.075E-02	6.141E-02	5.075E-02	4.582E-02
27.5	3.443E-02	3.424E-02	2.369E-02	3.424E-02	4.061E-02
32.5	2.629E-02	2.515E-02	1.459E-02	2.515E-02	1.440E-02
37.5	1.196E-02	1.275E-02	1.933E-02	1.275E-02	6.620E-03
42.5	3.388E-03	8.547E-03	5.700E-03	8.547E-03	4.698E-03
47.5	1.165E-02	8.524E-03	4.608E-03	8.524E-03	7.927E-03
55	3.345E-03	7.677E-03	1.040E-02	7.677E-03	1.322E-02
65	4.005E-03	4.359E-03	3.662E-03	4.359E-03	9.155E-03
85	7.168E-03	5.143E-03	4.981E-03	5.143E-03	1.643E-02
125	3.588E-03	2.987E-03	4.433E-03	2.987E-03	8.458E-03
225	4.340E-03	2.402E-03	1.996E-03	2.402E-03	1.255E-02
400	1.233E-03	2.056E-03	1.907E-03	2.056E-03	5.082E-03

References

[1] Druitt and früh - simulation of demand management and grid balancing.pdf.

[2] G.N. Bathurst and G. Strbac. Value of combining energy storage and wind in short-term energy and balancing markets. *Electric Power Systems Research*, 67(1):1–8, October 2003.

[3] David Biere, David Dallinger, and Martin Wietschel. Ökonomische analyse der erstnutzer von elektrofahrzeugen. *Zeitschrift für Energiewirtschaft*, 33(2):173–181, June 2009.

[4] George E. P Box, Gwilym M Jenkins, and Gregory C Reinsel. *Time series analysis : forecasting and control*. John Wiley, Hoboken, N.J., 4th edition, 2008.

[5] M. Carrion, J.M. Arroyo, and A.J. Conejo. A bilevel stochastic programming approach for retailer futures market trading. *Power Systems, IEEE Transactions on*, 24(3):1446 –1456, August 2009.

[6] M. Carrion, A.B. Philpott, A.J. Conejo, and J.M. Arroyo. A stochastic programming approach to electric energy procurement for large consumers. *Power Systems, IEEE Transactions on*, 22(2):744 –754, May 2007.

[7] Antonio J. Conejo, Miguel Carrión, and Juan M. Morales. *Decision Making Under Uncertainty in Electricity Markets*, volume 153 of *International Series in Operations Research and Management Science*. Springer, 1st edition. edition, September 2010.

[8] Antonio J. Conejo, Javier Contreras, Rosa Espínola, and Miguel A. Plazas. Forecasting electricity prices for a day-ahead pool-based electric energy market. *International Journal of Forecasting*, 21(3):435–462, July 2005.

[9] D. Dallinger, D. Krampe, and M. Wietschel. Vehicle-to-Grid regulation reserves based on a dynamic simulation of mobility behavior. *Smart Grid, IEEE Transactions on*, 2(2):302 –313, June 2011.

[10] David Dallinger and Martin Wietschel. Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles. *Renewable and Sustainable Energy Reviews*, 16(5):3370–3382, June 2012.

[11] Deutsches Institut für Wirtschaftsforschung. Mobilität in deutschland - ergebnisbericht. Technical report, 2008.

[12] B. Dietz, K. Ahlert, A. Schuller, and C. Weinhardt. Economic benchmark of charging strategies for battery electric vehicles. In *PowerTech, 2011 IEEE Trondheim*, pages 1 –8, June 2011.

[13] L.P. Garces and A.J. Conejo. Weekly Self-Scheduling, forward contracting, and offering strategy for a producer. *Power Systems, IEEE Transactions on*, 25(2):657 –666, May 2010.

[14] A. C Harvey. *Time series models*. Harvester Wheatsheaf, New York; London, 1993.

[15] Holger Heitsch and Werner Römisch. Scenario reduction algorithms in stochastic programming. *Computational Optimization and Applications*, 24(2):187–206, 2003.

[16] J.M. Morales, A.J. Conejo, and J. Perez-Ruiz. Short-Term trading for a wind power producer. *Power Systems, IEEE Transactions on*, 25(1):554 –564, February 2010.

[17] Salvador Pineda-Morente. *Medium-Term Electricity Trading for Risk-Averse Power Producers via Stochastic Programming*. Phd. thesis, Universidad de Castilla-la Mancha, Department of Electrical Engineering, 2011.

[18] Di Wu, D.C. Aliprantis, and K. Gkritza. Electric energy and power consumption by Light-Duty Plug-In electric vehicles. *Power Systems, IEEE Transactions on*, 26(2):738 –746, May 2011.