Chapter 8
Towards a Business Case for Vehicle-to-Grid—Maximizing Profits in Ancillary Service Markets

David Ciechanowicz, Alois Knoll, Patrick Osswald and Dominik Pelzer

Abstract Employing *plug-in electric vehicles* (PEV) as energy buffers in a smart grid could contribute to improved power grid stability and facilitate the integration of renewable energies. While the technical feasibility of this concept termed *vehicle-to-grid* (V2G) has been extensively demonstrated, economic concerns remain a crucial barrier for its implementation into practice. A common drawback of previous economic viability assessments, however, is their static approach based on average values which neglects intrinsic system dynamics. Realistically assessing the economics of V2G requires modeling an intelligent agent as a homo economicus who exploits all available information with regard to maximizing its utility. Therefore, a smart control strategy built on real-time information, prediction and more sophisticated battery models is proposed in order to optimize an agent's market participation strategy. By exploiting this information and by dynamically adapting the agent behavior at each time step, an optimal control strategy for energy dispatches of each single PEV is derived. The introduced cost-revenue model, the battery model, and the optimization model are applied in a case study building on data for Singapore. It is the aim of this work to provide a comprehensive view on the economic aspects of V2G which are essential for making it a viable business case.

Keywords Vehicle-to-grid · Plug-in electric vehicle · Economic viability · Ancillary services · Battery modeling · Optimization model

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8.1 Introduction

In power systems, fluctuations of energy demand and supply cause continuous deviations from the desired frequency. Ensuring power grid stability requires an instantaneous response by the power system operator which restores the equilibrium between demand and supply. This is either achieved by power plants capable of quickly adjusting their power output or by storage facilities which buffer energy excesses or shortages. Most of these solutions are, however, either costly, entail large space or exhibit low energy efficiencies leading to the need for development of alternative approaches.

One possible solution could be the utilization of *plug-in electric vehicles* (PEV) of which batteries could be employed as short term energy storage through charging in the case of a power excess or by feeding electricity back to the grid in the opposite case. This concept termed *vehicle-to-grid* (V2G) was first mentioned in 1997 [1] and has been subject to intensive research in the last two decades. While the effectiveness of the V2G concept to improve power grid stability has been confirmed by both theoretical considerations [2–8] as well as fully functional prototypes [5, 7, 9], its economic viability is still subject to controversial discussions. This is reflected in the diverging conclusions on the profitability where some expect annual losses of several thousand dollars while others promise multiple thousand dollars of yearly income [2, 6, 9–15].

One drawback of previous economic analyses of the V2G concept is that calculations are based on average annual values for the involved parameters. In reality, however, electricity prices highly vary during the course of a day, presenting varying scenarios where V2G may yield profits in one time period but result in losses in a different one. Furthermore, individual travel itineraries impose restrictions on the temporal availability of PEVs. At the same time, factors such as battery aging typically depend non-linearly on a variety of parameters which cannot be kept constant during V2G operation. Simple averaging therefore does not yield correct cost estimations. The entity of these aspects significantly limits the explanatory power of static approaches and leaves the outcome of these methods highly sensitive to the choice of the input parameters. To correctly determine the economic viability of V2G and at the same time provide a control strategy for individual V2G agents, more dynamic approaches are required.

The purpose of this chapter is to discuss the problems of previous approaches investigating the economic viability of V2G and to identify solutions that could pave the way for making V2G an economically viable business case. The remainder of this work is structured as follows: In Sect. 8.2, the transition from a power system to a smart grid is described. In this context, the V2G concept is discussed as one possible future solution for improving power grid stability. Section 8.3 introduces an electricity market independent V2G control strategy which aims for maximizing profits in ancillary service markets. This concept includes an appropriate consideration of battery depreciation as well as an optimization methodology. The optimization model is then applied in a simple case study building on data for

Singapore in Sect. 8.4, followed by a discussion of parameter sensitivities. In Sects. 8.5 and 8.6 findings are finally discussed and an outlook on future research is given.

8.2 Power System Fundamentals

In the first part of this section, the fundamentals of the power system and the concept of ancillary services are briefly introduced. It is discussed, how the transition to a smart grid could mitigate the increasing need for balancing power demand and supply which arises from the growing share of renewable energy sources. This leads to the possible role of PEVs and the V2G concept in the future power grid, which is described in more detail in Sect. 8.2.2. One important component for the implementation of V2G is the aggregator which is finally discussed in Sect. 8.2.3.

8.2.1 Power System and Smart Grid

A *power system* is a network of power lines which connect energy producing and consuming entities with each other. Different voltage levels may distinguish the power grid into a maximum, high, medium, and low voltage grid with the first two levels forming the *transmission grid* and the latter two the *distribution grid*. The different levels are physically separated from each other by substations, switches, and transformers and are controlled by high performance computers.

In Fig. 8.1 a rough illustration of the Singapore power system as it can be derived from data on high-voltage grid, substations and consumers is exemplarily shown. The upper layer shows the transmission grid while the middle layer depicts

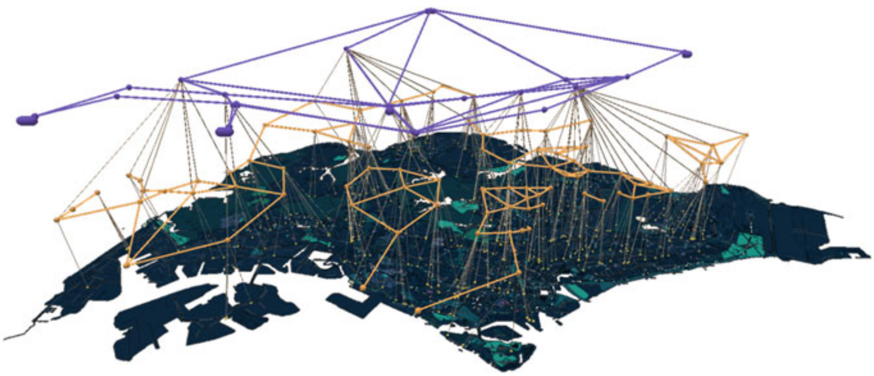


Fig. 8.1 Singapore power system

the distribution grid. The nodes in both layers represent power plants, substations, switches or transformers which in this case are not visually distinguished. The nodes at the bottom layer on the map depict a selection of consumers connected to the distribution grid.

A power grid is operated by one or more *transmission system operators* (TSO) of which its primary task is the energy transfer from the generation units to regional or local *distribution system operators* (DSO) which then deliver the energy to the consumers. One key responsibility of a TSO is to ensure power grid stability. The power grid itself only exhibits negligible energy storage capacity and is therefore an inherently unstable system. Deviations between energy demand and supply which may either be positive when supply exceeds demand or negative in the opposite case therefore lead to fluctuations of voltage and frequency which require an immediate action. This response is performed by so called *ancillary services* provided by fast responding power generators which are capable of quickly ramping up or curbing down their power output. Depending on the response time and the duration of providing ancillary services, it is distinguished between *regulation* as well as *primary*, *secondary*, and *contingency reserve*. All of the four markets usually have a ratio of around 1 % of the total annual energy generation. Providers of ancillary services receive a payment for the dispatched energy when up-regulation is required or a compensation for curbing power generation in the opposite case. These *energy payments* are usually differentiated and considerably higher for regulation than for reserve. Besides these energy payments, many national electricity markets also have a *capacity payment* which is a reward solely for holding power generation potential available instead of energy dispatch. In most markets, prices are fairly variable over time but are kept constant for a certain time period of 15 or 30 mins in most cases.

As a result of growing shares of intermittent renewable energy sources and the introduction of PEVs on a large scale, the need for ancillary services and energy storage is increasing. This is because both the availability of renewable energies and the mobility pattern of PEVs are volatile and sometimes hard to predict. To satisfy the additional demand for ancillary services, either fast reacting generators or energy storage facilities are needed. Technologies capable of providing this functionality include *pumped storage hydroelectricity* (PSH), *compressed air energy storage* (CAES), *hydrogen-driven fuel-cells*, or *supercapacitors*. These technologies are, however, often costly, energy inefficient or may entail large space leading to the need for alternative approaches.

The need for energy storage may be reduced in a smart grid which supports multi-directional energy flow instead of showing a strictly hierarchical topology. In this case, energy is not only generated at the high voltage levels but may also be provided by generators within the distribution grid. These generators could then also serve as ancillary service providers so that large power plants could keep operating at their optimal efficiency. With a communication infrastructure allowing the intelligent control of energy producers and consumers this would lead to a distributed, self-organizing grid design.

One important role in a future smart grid could be taken by PEVs which have the capability of acting as either consumers or producers by using their battery as energy buffers. PEVs are advantageous compared to classical generators in the way that they can react to demand requests virtually in real-time, have low standby and initial costs per kWh, and provide temporarily high power. With a sufficient amount of PEV participating in V2G services, capacities from conventional power sources would therefore become redundant. This V2G concept will be introduced in greater detail in the following section and will be further assessed in the remainder of this chapter.

8.2.2 The V2G Concept

The V2G concept is depicted in Fig. 8.2. Energy is generated by conventional power plants or renewable energy sources and transmitted through maximum, high, medium and low voltage lines to the consumers (e.g., households, enterprises, charging stations, etc.). The type of consumers that is of interest in this context are PEVs which may either use the energy for driving or serve as a short-term energy storage by charging their battery packs in case of power excess or feeding electricity back in the opposite case. Discharging a PEV's battery during an energy shortage and therefore providing energy to the grid is called V2G while charging the battery during an energy excess is known as *grid-to-vehicle* (G2V). The V2G concept incorporates both services so this term will be used within this chapter whenever no explicit distinction is necessary. In the following, four scenarios are introduced in which possible use cases for the energy stored in the battery packs of the PEVs are outlined.

Scenario A depicts a one-way flow of energy where a PEV is simply charged at a charging station installed in a household. Scenario B uses the same setting but in addition energy can be locally fed back to the household. This concept is termed *vehicle-to-home* (V2H). The case of allowing energy to flow back into the power grid representing the V2G concept is depicted in Scenario C. In this case, the PEVs communicate with an intelligent charging station which then dispatches or draws energy to or from the PEV. The charging station itself is controlled by an aggregator which is a unit that bundles multiple PEVs to a *virtual power plant* (VPP) [7, 16–19] in order to trade energy at the electricity market. Due to its important role, the aggregator is discussed in further detail in Sect. 8.2.3. In Scenario D, multiple PEVs are aggregated to a VPP through an operator of e.g. a car park. This operator could use the aggregated energy as described by the V2H concept, directly participate in the energy market or could again be part of a VPP of some higher level aggregator.

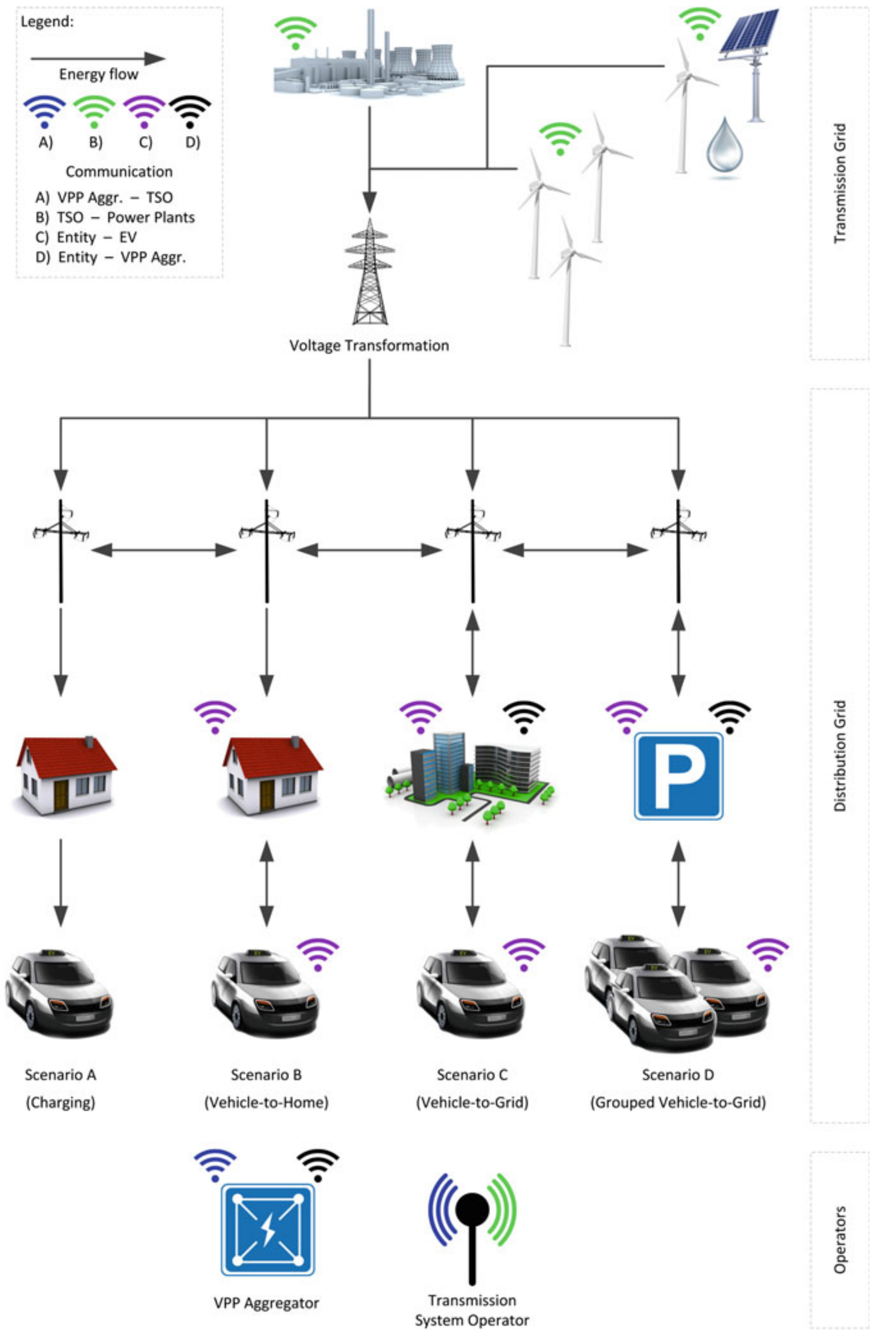


Fig. 8.2 The V2G concept

8.2.3 The Aggregator

The amount of energy and power each individual PEV can provide is too small to participate on most electricity markets (in Singapore 1 MW for half an hour is necessary). Meeting these conditions thus requires hundreds to thousands of PEVs aggregated to a VPP. This is achieved by an aggregator who serves as a mediator between the PEVs and the electricity market. The aggregator trades energy at the market and ensures that the VPP is capable of providing the contracted power at all times. An aggregator should be considered a virtual entity rather than a physical one. This means that the PEVs belonging to one aggregator do not necessarily need to be connected at neighboring locations. Instead, aggregation at the level of the same grid node or even only in the operation range of one grid operator may be sufficient in many electricity markets. In addition to PEVs, an aggregator could have access to other energy sources e.g. secondary market battery packs, conventional or renewable energy power plants or other sub-aggregators. From the TSO's point of view, the power generation capacity offered by the aggregator presents itself as a single large, fast-controllable energy source although it may originate from a variety of different sources. The relation between all involved actors is depicted in Fig. 8.3.

The challenge faced by the aggregator is to synchronize charging and discharging operations of a large number of PEVs in order for all PEVs to reach their targeted state of charge, while ensuring that the contracted ancillary services can be provided at all times. Due to the continuous fluctuation of the number of PEVs in the VPP, the heterogeneity of the carpool and the fact that both aggregator and PEV owners aim to maximize their profit, this leads to an optimization problem with a high degree of uncertainty. Since each PEV typically has its individual utility function and own constraints, a central control mechanism would quickly become

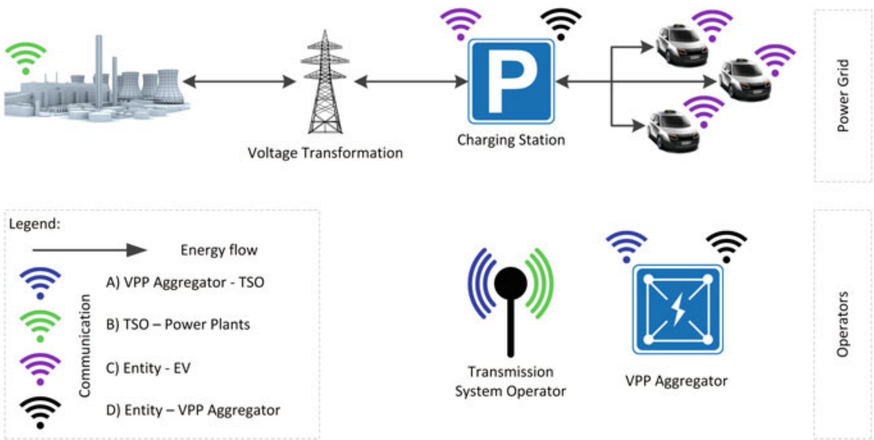


Fig. 8.3 The aggregator concept

infeasible. Therefore, a distributed approach where each PEV performs its individual optimization is discussed in Sect. 8.3.3. As such, the central remaining task of the aggregator is to achieve sound estimations on the demand and power generation capacity of its VPP and, if necessary, trigger behavior changes of the involved PEVs in case it is at risk of failing to fulfill its obligations to the TSO.

Influencing the charging and dispatching behavior of PEVs which are part of the VPP can be achieved by sending price signals which may not necessarily correspond to market prices. By decoupling prices offered by an aggregator from prices given by the electricity market, the temporal gap between a period in an electricity market in the range of minutes and the requirements for regulation on a scale of seconds can be closed. Real-time prices would also allow an aggregator to dynamically adapt the charging/dispatching power of each individual agent in real-time and not only on a period basis. Based on historical data collected by an aggregator, the algorithm would have to take an estimate of the temporal availability of each PEV as well as each agent's individual cost function and battery capacity constraints into consideration. In return, it may produce an optimal charging/dispatching schedule for each point in time optimizing its own profits by also generating (not necessarily optimal) profits for each agent.

Presuming V2G is a profitable concept, there are different types of entities that might be interested in establishing themselves as aggregators. First of all, battery pack or vehicle manufacturers have detailed knowledge about their battery inherent depreciation cost functions. The drawback of the two parties is the spatial distribution of their aggregated PEV fleet which might cause problems with feeding energy into the right section of the low voltage grid. Additionally, they may lack necessary know-how in the area of communication. Another group of interest could be mobile network operators and DSOs which both have expertise regarding communication technology and accounting systems, especially with a large amount of small-size customers. Additionally, DSOs already have a business connection with customers in the energy segment. Particularly advantageous for DSOs is their profound knowledge of power demand and supply in the grid. At last, entities who command a sufficiently large PEV fleet could promote themselves being an aggregator. Their advantage is their knowledge about the tempo-spatial availability of each PEV.

8.3 An Intelligent Agent Behavior Model

One essential criterion for making the V2G concept applicable in practice is to prove its economic viability on one hand and on the other to provide individual agents with a control strategy which maximizes their profit. For this purpose, in Sect. 8.3.1 the basic equations for an economic model for V2G are introduced. Section 8.3.2 then discusses the challenges and approaches regarding battery aging models which are a crucial factor for assessing the costs of V2G. In Sect. 8.3.3 it is then described, how the introduced equations can be utilized for a dynamic control strategy which most effectively exploits the economic potential of V2G for an individual user. Section 8.3.4 finally briefly discusses what role artificial intelligence could play for making V2G applicable in practice.

8.3.1 Economic Model

In this section, the equations which are used for investigating the economic viability of V2G valid for most electricity markets are introduced [20]. Total annual profits are calculated from the difference between revenues R and costs C

$$\prod = R - C \tag{8.1}$$

which are separately discussed in the following two sections.

8.3.1.1 Revenues

The total revenue R is the sum of the revenues made from up-regulation and the revenues attained from down-regulation services. In the event of an under-supply of power, up-regulation is necessary. In this case, the PEV acts as a generator and feeds energy into the grid. Therefore, energy is sold at the regular selling price in the respective electricity market p_E plus a compensation for providing up-regulation ancillary services $p_{\uparrow,\mathrm{Anc}}$. Depending on the energy market under consideration, $p_{\uparrow,\mathrm{Anc}}$ corresponds to either the payment for reserve or regulation. In this case, the received payment per unit of dispatched energy is

$$p_{\uparrow,E} = p_E + p_{\uparrow,\mathrm{Anc}} \tag{8.2}$$

In the opposite case where power supply exceeds demand, down-regulation is required and the PEV acts as a consumer. The owner pays the electricity tariff p_{ET} which is discounted by the down-regulation compensation $p_{\downarrow,\mathrm{Anc}}$. Since the energy purchase costs given by p_{ET} are explicitly accounted for in Sect. 8.3.1.2, the effective payment per unit of energy in this case is therefore simply

$$p_{\downarrow,E} = p_{\downarrow,\mathrm{Anc}} \tag{8.3}$$

In many national electricity markets, additional capacity payments $p_{\uparrow,\mathrm{Cap}}$ and $p_{\downarrow,\mathrm{Cap}}$ are provided for only holding power generation potential available rather than actually dispatching energy.

The total annual revenue R is the sum of the revenues resulting from the energy and the capacity payment. Each of the two payments has to be multiplied by the respective amounts of purchased and dispatched energy, or stand-by power. As previously discussed, market prices are typically time-dependent but remain constant for time periods of a certain duration Δt. As a simplification, the charging/dispatching power may also be assumed to be kept unchanged during one time period. The total annual revenue R over all time periods i can then be written as

$$R = \sum_i \left(p_{\uparrow,E,i} P_{\uparrow,E,i} + p_{\uparrow,Cap,i} P_{\uparrow,Cap,i} + p_{\downarrow,E,i} P_{\downarrow,E,i} + p_{\downarrow,Cap,i} P_{\downarrow,Cap,i} \right) \cdot \Delta t \tag{8.4}$$

8.3.1.2 Costs

The total annual costs C_A are calculated as the variable costs $c_{var} = c_\eta + c_D$ multiplied by the total annual amount of energy cycled through the battery pack E_A, plus annual fixed costs C_{AF}:

$$C_A = E_A \left(c_\eta + c_D \right) + C_{AF} \tag{8.5}$$

In this equation, c_η denotes the energy purchase costs which, using the charge-discharge efficiency η, can be written as

$$c_\eta = \frac{p_{ET}}{\eta} \tag{8.6}$$

The term c_D represents the variable battery pack depreciation costs which result from the limited number of possible charge-discharge cycles. Using the purchase costs of a battery pack $C_{\text{BatterPack}}$ and the total possible energy throughput E_{Lifetime}, this turns into

$$c_D = \frac{C_{\text{BatteryPack}}}{E_{\text{Lifetime}}} \tag{8.7}$$

The quantity of energy which can be cycled through a battery pack until it fails to meet its specific performance criteria is given by the capacity $Q_{\text{BatteryPack}}$ multiplied by the *depth of discharge* (*DOD*) and the maximum number of cycles Z possible at a certain DOD:

$$E_{\text{Lifetime}} = Z \cdot DOD \cdot Q_{\text{BatteryPack}} \tag{8.8}$$

One cycle in this context is understood as discharging the battery from an initial *state of charge* (SOC) by a certain DOD and subsequently recharging it to the initial SOC; the charge throughput per cycle therefore depends upon the corresponding DOD. The cycle stability Z is a quantity which depends on a large number of parameters such as *charge rate* (C-rate), DOD, temperature, humidity and time and which strongly varies among different battery chemistries [21]. It is therefore not possible to reliably model the cyclic lifetime so that many studies simply assume a fixed number for Z [6, 10, 12, 13]. In Sect. 8.3.2 the challenges related to battery lifetime modeling are discussed in further detail.

The last term of (8.5) C_{AF} denotes the fixed costs which account for the investment in equipment required to make a PEV suitable for V2G. To annualize and discount the fixed costs, it can be written as

$$C_{AF} = C_C \frac{d}{1 - (1 + d)^{-n}} \tag{8.9}$$

with C_C being the total capital costs, d the discount rate and n the number of years until the investment is depreciated. With these considerations, the total annual costs can finally be rewritten as

$$C_A = E_A \left(\frac{p_{ET}}{\eta} + \frac{C_{\text{BatteryPack}}}{Z \cdot DOD \cdot Q_{\text{BatteryPack}}} \right) + C_C \frac{d}{1 - (1 + d)^{-n}} \tag{8.10}$$

8.3.2 Battery Modeling

A crucial aspect for the profitability of V2G applications is battery degradation cost. To appropriately consider the costs of battery degradation in an economic model and to account for these costs during V2G operation, an understanding of battery aging processes and their representation by a suitable battery model is required.

The performance fade of a cell can be separated into the loss of capacity (measured in Ah) as well as the increase of the cell impedance which causes energy fade (measured in Wh) and power fade (measured in W). The main effect for capacity fade is the loss of cyclable lithium, primarily caused by formation of the *solid electrolyte interface* (SEI) at the graphite anode [22, 23] as well as by lithium plating occurring at high charging currents and low temperatures. This loss of cyclable lithium in turn causes a change of the electrode balancing, preventing the battery from being fully charged and discharged at specific current rates [24]. The second contributor to capacity fade is the loss of active electrode material. When the cell is cycled at high and low SOCs, the electrodes undergo certain mechanical stress during lithium intercalation, resulting in micro cracking. These micro cracks lead to either further SEI formation or can cause a loss of contact for the active material, making them unavailable for further intercalation processes [22, 23, 25]. In addition to the capacity fade described, these mechanisms are closely correlated to the increase of the cell impedance. The ongoing SEI reformation causes a constantly growing surface layer with a low conductivity and low diffusivity, causing an increase in the charge transfer resistance [25]. The loss of active material leads to higher local currents and local SOC variations, which in turn accelerate the aging process [26].

These different aging mechanisms are triggered from the environment and the utilization mode, including the cell's temperature, the DOD, the charge and discharge current rate as well as the SOC range the cell is used in [25, 27–29]. In general, high currents as well as extremely high and low SOC conditions accelerate the aging process of the cells; high temperatures accompanying these high currents lead to an increased amount and speed of parasitic side reaction. An intelligent V2G control strategy would therefore aim at maintaining moderate SOC conditions, avoiding extreme DODs and keeping charge and discharge currents low.

Numerous studies have been performed to understand these mechanisms and to establish a quantitative relation between these aging effects and the corresponding control parameters [29, 30]. Battery aging studies considering multiple parameters are, however, complex and very time consuming, particularly at low C-rates. Hence, certain drawbacks in the accuracy of the battery aging model have to be taken into account. As a first approach, it can be assumed that the aging of the cell is dominated by the charge throughput during charge and discharge of the cell. As described earlier, the rate of damage is greater at extremely high and low SOCs which can be reflected in a DOD dependent aging parameter.

To quantitatively account for battery depreciation costs due to charging and discharging, the cost of a unit of cycled energy needs to be computed according to (8.7). A simple empirical model for battery aging which is employed in the sensitivity analysis of the case study presented in this paper was developed by Peterson and Whitcare [31]. In this model, the cyclic stability introduced in (8.8) is given as

$$Z(DOD) = \left(\frac{145.71}{DOD}\right)^{\frac{1}{0.6844}} \tag{8.11}$$

which explicitly considers the effect of the DOD on the possible number of cycles.

While the DOD can be assumed to be the most relevant parameter, the battery aging estimation can be further improved by additionally taking the non-linear behavior of the SOC-dependent aging into account. This is achieved by a model presented in [32] which was adapted to be employed in the case study in Sect. 8.4. It describes the battery capacity fade due to cyclic aging as a function of the charge throughput q according to the relation

$$CAP(q) = 1 - \beta \cdot \sqrt{q} \tag{8.12}$$

where CAP denotes the battery capacity and where β is an experimentally determined factor which was found to be

$$\beta = 7.348 \times 10^{-3} \cdot (\bar{U} - 3.667)^2 + 7.6 \times 10^{-4} + 4.081 \times 10^{-3} \cdot DOD \tag{8.13}$$

for the investigated battery type.

In this equation, $\bar{U}$ is the average voltage at which the cycling occurs which can be obtained from the open-circuit voltage of the battery cell. As $\bar{U}$ depends on the SOC, this relation implicitly accounts for the SOC as a second parameter apart from the DOD. Setting $CAP(q) = 80\,\%$ which is a common criterion for the end of life of batteries used for automotive applications then allows calculating E_{Lifetime}. This ultimately leads to the following equation for battery depreciation costs

$$c_D = C_{\text{BatteryPack}} \cdot \frac{\beta^2}{0.04 \cdot \overline{\overline{U}}} \tag{8.14}$$

which consider both DOD and SOC.

8.3.3 *Optimization*

Cost and revenue equations similar or equivalent to the ones discussed in the previous sections have been applied in many cases to assess the economic viability of V2G. This has mostly been accomplished by using average values for prices, battery lifetime and charging and dispatching power. Most of the studies relying on realistic assumptions conclude that the PEV owner would incur monetary losses from providing V2G services. It is therefore clear that control strategies based on this averaging behavior would not lead to a valid business case. Control strategies for V2G need to be directly related to economic considerations to give the V2G concept a chance to be implemented in practice at all. This means that strategies need to account for the temporal dynamics of the market and need to reflect the behavior of intelligent agents who would attempt to maximize their profits by adapting to these fluctuations.

The resulting question therefore is how rational agents would decide on their charging and dispatching strategies presuming they have certain information on internal and external parameters. Technically, this means that a cost-benefit calculation according to the equations defined above needs to be conducted whenever any change of the relevant parameters occurs.

There have been several recent attempts in the literature which address this issue [15, 33]. A simple strategy which improves the loss-making averaging approach is to make a binary decision on when to provide V2G services, depending on whether the evaluation of the cost model yields an expected benefit or a loss. Given an additional degree of freedom where the user cannot only make a binary decision but continuously adapt the power output or input, a next step is to compute an optimal value for the charging or dispatching power for a certain point in time. This approach can be refined further by making use of predictive information. In most electricity markets, price estimates for buying and selling electricity are known a certain period of time in advance. This information may be used by an intelligent agent to decide when and at what power to charge or discharge its battery in order to achieve the greatest possible profit. The agent may then even accept losses in some periods to attain higher profits in the following ones. Technically, this can be formulated as a mathematical optimization problem with various constraints.

The function to be maximized is the profit Π which can be attained during a certain number of time periods T. Since electricity prices fluctuate over time, revenues and costs according to (8.4) and (8.10) can be expected to be different in each time interval so that the profit has to be written in the form

$$\Pi = \sum_{i=1}^{T} (R_i(P_i) - C_i(P_i)) \tag{8.15}$$

In a simple scenario, the power P_i in a certain time interval is limited by the maximum C-rate defined by the battery specifications and by an SOC constraint which determines how much energy can be charged into the battery or dispatched to the grid. The optimization problem can then be written in the form

$$\begin{aligned} &\underset{P_i}{\text{maximize}}\ \Pi \\ &\text{subject to } P_{\min} \le P_i \le P_{\max} \\ &\text{and } 0 \le SOC_i \le 1 \end{aligned} \tag{8.16}$$

The SOC change between two time steps is simply calculated according to the relation

$$SOC_i = SOC_{i-1} + \frac{P_i \cdot \Delta t}{Q} \tag{8.17}$$

A more sophisticated control strategy should also account for time periods at which the PEV is expected to be in use. This leads to additional constraints which ensure that the battery contains enough energy to complete the next trip. Given a battery capacity Q and energy consumption e, a trip starting at time interval m with an expected driving distance d implies the following condition for the SOC at time interval $m - 1$:

$$SOC_{m-1} \ge \frac{e \cdot d}{Q} \tag{8.18}$$

During the trip from time interval m to n no grid connection can be established so that

$$P_i = 0 \ \forall i : m \le i \le n \tag{8.19}$$

The SOC change between the start and the end of the trip is then calculated by

$$SOC_n = SOC_m - \frac{e \cdot d}{Q} \tag{8.20}$$

In general, due to the non-linearity of realistic battery aging models, this problem has to be treated as a non-linear optimization problem. It may therefore either be addressed by a non-linear solver, or be piecewisely linearized and then be solved using a linear solver.

8.3.4 Artificial Intelligence

Given the dynamics of the system and complexity of the problem, the decision on whether to charge or discharge the battery needs to be automatized by an intelligent control unit in the PEV [19]. This control system should not only be capable of performing the mathematical optimization but should also be able to autonomously define the optimization constraints. One example for these constraints is the battery SOC required for driving. A user cannot be expected to be willing to manually specify the time, duration and expected energy consumption of the next trip. Instead, the system needs to be able to make appropriate predictions which ensure that the user does not run out of energy at any point in time. The better the prediction quality, the higher the expected profits because safety buffers can be kept small resulting in more battery capacity being available for V2G. This prediction, however, needs to be tailored to every individual user. Different users have different driving patterns, different driving styles and corresponding differences in energy consumption. Some may exhibit very regular commuting patterns while others might have highly varying itineraries. Different agents would therefore require different V2G strategies. In order to facilitate V2G, intelligent mechanisms are thus required to keep the user free of these concerns.

Artificial intelligence may also be beneficial in the context of price prediction. While 24 h predictions of electricity prices are available in a day ahead market, these are generally subject to an error which grows with the number of lookahead periods. Using these predictions may therefore compromise optimization efforts. With an increasing number of individual market participants, the market can be expected to gain additional dynamics that may further increase this error. For best optimization results it would therefore be crucial for an intelligent system to provide error estimations for certain times and locations. Also aggregators may require machine learning mechanisms in order to optimize their bids at the electricity markets.

8.4 Case Study

In this section, the cost and revenue model is applied to the electricity market data of Singapore using the optimization model from Sect. 8.3.3. The purpose of this case study is to demonstrate how different models and parameters lead to highly different conclusions on the economic viability of the V2G concept and to show how previous studies relate to a model which accounts for the dynamics of the problem. This case study should not be considered a thorough economic viability analysis of the V2G concept. Instead, its purpose is to create a sense for the influence of certain parameters and therefore demonstrate the importance of choosing models and parameters with care.

Due to the non-linearity of the battery model and the existence of integer variables, the optimization problem is treated as a *mixed integer non-linear program* (MINLP). The problem was implemented in the *general algebraic modeling system* (GAMS) and the COUENNE solver was used for optimization.

General parameters that are used for the optimization model are described in Sect. 8.4.1. Section 8.4.2 then introduces the specific electricity market data of Singapore. Findings of this case study are discussed in different scenarios in Sect. 8.4.3. Since several of the mentioned parameters broadly disperse in reality and are expected to change over time, the general parameters are varied as part of the sensitivity analysis presented in Sect. 8.4.4.

8.4.1 General Parameters

In all calculations of the case study, a battery pack capacity of 20 kWh is assumed. This is in accordance with the battery dimensions of the Nissan Leaf (24 kWh), the Mitsubishi i-MiEV (16 kWh), or the BMW i3 (18.8 kWh). The battery pack replacement costs are set to S$ 770[1] per kWh which reflects present prices according to [34, 35]. Additional equipment that enables PEVs to provide V2G services is expected to yield fixed costs of at most a few hundred S$. These costs are negligibly low when prorated over the whole lifetime of the battery pack and are therefore not considered in this case study.

As described in Sect. 8.3.3, power is treated as a continuous variable in the model and is kept in the range between −40 and +40 kW. This ensures a maximum C-rate of 2C meaning that the battery pack can be fully charged or discharged within half an hour. The energy efficiency of a charge-discharge cycle is determined by the efficiency of charging and discharging electronics as well as the efficiency of the battery pack. In the given C-rate range, the efficiency can be considered the same for charge and for discharge processes [36, 37]. In accordance with values from this literature, the total energy efficiency of a charge-discharge process is set to $\eta = 0.80$. The cycle stability model used for the assessment of the V2G concept in this case study was already described in Sect. 8.3.2. Prices for the different energy markets are described in Sect. 8.4.2.

[1] S$ 1 equals 0.80 USD (November 6, 2014).

8.4.2 Market Data

In Singapore, energy is traded at the *national electricity market singapore* (NEMS) which is controlled by the *energy market authority* (EMA) [38]. As already discussed in Sect. 8.2.1, this case study focuses on the ancillary service market. Depending upon the response time and the duration of providing ancillary services, the market distinguishes between *regulation* as well as *primary*, *secondary*, and *contingency reserve* [39]. When buying electricity from a generator an entity has to pay the *uniform singapore energy price* (USEP). This is considered the energy payment an entity receives when offering up-regulation [see (8.2)]. For the opposite case of down-regulation, no energy payment is provided [see (8.3)]. In addition to the energy payment, there is a compensation for holding power generation or remission potential available. This capacity payment is called *market regulation price* (MFP) and *market reserve price* (MRP) for regulation and reserve, respectively. While there is only one MFP, a distinct MRP is associated with each of the three classes of reserve. Due to the lack of concrete data it is assumed that offered energy will be entirely dispatched. This is to ensure that participants in the NEMS only earn money if they actually dispatch energy.

The electricity market price data used in this study cover the USEP, MFP and all classes of MRP for the entire year 2012 [40]. At the NEMS, all of these prices are adjusted on a half-hourly basis so that all presented calculations build on time series with a 30-min resolution, dividing one day in 48 periods. These prices are known 24 h in advance with an increasing average deviation, depending on the lookahead time. Calculations in this case study are based on a lookahead of 2 periods having a mean uncertainty of slightly above 1 ‰. Additionally, the end-consumer price for electricity, called *electricity tariff* (ET), is used. It mainly consists of energy costs (82 %) as well as transmission costs (17 %) and is subject to quarterly adaptation. To provide a rough overview of these prices and their temporal variance, their average values as well as standard deviations are given in Table 8.1.

8.4.3 Results

In the simplest possible scenario, a PEV is grid-connected 24 h per day, 365 days a year. It can therefore be considered a stationary energy buffer with a service level

Table 8.1 Key figures of the NEMS price data in 2012

	ET [S$/MWh]	USEP [S$/MWh]	MFP [S$/MWh]	MRP [S$/MWh]		
				Primary	Secondary	Contingency
Average	279.3	222.49	91.53	0.33	1.37	11.40
Standard deviation	5.69	112.92	40.35	2.26	4.48	64.86

agreement on availability of 100 %. Although this assumption is fairly unrealistic, it allows an upper bound estimate on the economic attractiveness of the different ancillary service types introduced in Sect. 8.2.1.

An illustration of the functioning of the method can be found in Fig. 8.4a–d which exemplarily shows the optimization result for a period of two days. Figure 8.4a depicts the MFP and USEP. In this figure it can roughly be distinguished between four different regions, the first exhibiting high prices, the second showing a period of lower prices and another high price period followed by a region of again lower prices. In Fig. 8.4b, the calculated optimal power is shown. It can be seen that during high price periods high charging and discharging power is applied while power remains low or even zero in the low price regions. The alternation between charging and discharging is due to the SOC constraint and ensures that the cycling occurs at moderate SOC levels. Naturally, as shown in Fig. 8.4c, profits in each time period follow the power curve. Oscillations into the negative direction are, however, fairly moderate since the compensation for down-regulation is credited. Figure 8.4d shows the accumulation of profits over time. The oscillations occur because losses are accepted in one period in order to make even higher profits in another. With increasing lookahead, these oscillations can be expected to become less regular since the algorithm has a higher degree of freedom for optimizing profits.

The outcome of the analysis for the different energy markets of Singapore can be found in Table 8.2. Results for all of the three reserve markets show that annual profits in the range from S$ 177 to S$ 912 can be gained. A large fraction of those

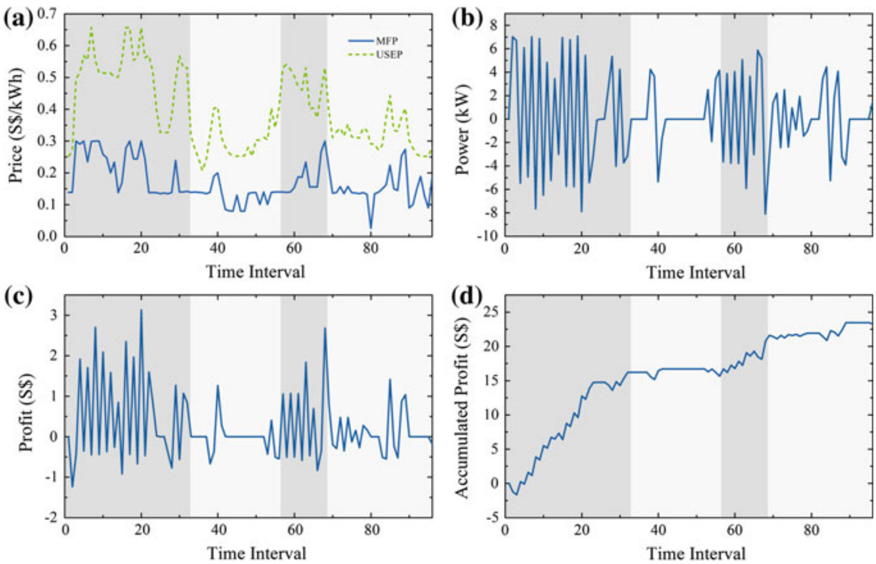


Fig. 8.4 Exemplary illustration of the optimization result for a time period of two days regarding **a** prices, **b** power, **c** profit and **d** accumulated profit

Table 8.2 Profits in different electricity markets regarding the simple scenario

Market	Profits [S$/year]	Profits, adjusted[a] [S$/year]
Reserve, primary	177	0
Reserve, secondary	183	0
Reserve, contingency	912	36
Regulation	394	109

[a] Extraordinarily profitable periods are left out

profits, however, results from just a dozen extraordinarily profitable periods which are most likely the outcome of a disruption in the power system. Leaving out those periods would result in annual profits of only up to S$ 36 for the contingency reserve and no profit at all for primary and secondary reserve. The reserve market is therefore not of interest for an economic application of the V2G concept and can be neglected in further analyses. For the regulation market the situation is more beneficial so that up to S$ 394 can be gained per year. Again, by neglecting the highest-price periods annual profits decrease to S$ 109.

To illustrate the fluctuations of achievable profits, Fig. 8.5 shows revenues and variable costs for one exemplary week in March 2012 for a fixed charging/dispatching power of 2 kW. It can be observed that revenues are highly variable over time. Some of these fluctuations have a considerable impact on annual income which leads to the discrepancy between profits and adjusted profits shown in Table 8.2.

A more realistic scenario assumes typical commuting habits of the population of the area of investigation. Therefore, mobility patterns of Singapore residents representing about 90 % of the population are used [20]. These patterns describe the trips various groups of people undertake on different days of the week. In particular, the data specify the start and end time of a trip as well as the type of destination categorized by *home*, *work* and *leisure*. This reveals information on the time windows at which PEVs can be connected to the grid depending upon the availability of charging stations at the various types of destinations.

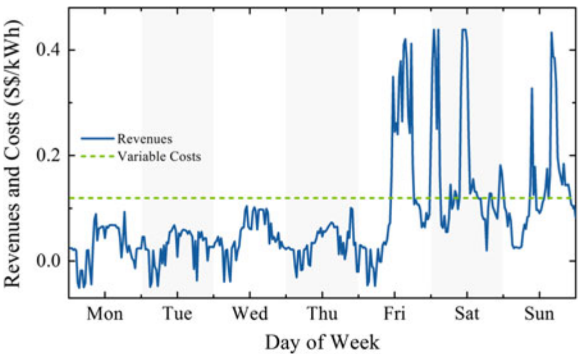


Fig. 8.5 Exemplary illustration of revenues and variable costs at fixed charging/dispatching power for a week in March 2012

Table 8.3 Profits in different electricity markets for the mobility pattern-based scenario

Market	Profits [S$/year]	Profits, adjusted[a] [S$/year]
Reserve, primary	60–178	0
Reserve, secondary	128–171	0
Reserve, contingency	597–863	21–25
Regulation	262–357	71–90

[a] Extraordinarily profitable periods are left out

Findings for different electricity markets regarding the mobility pattern-based scenario are presented in Table 8.3. Results for all of the three reserve markets show an annual profit in the range from S$ 60 to S$ 863, depending on the market and the applied mobility pattern. In the regulation market, annual profits lie in the range from S$ 262 to S$ 357. In the mobility pattern based approach, highest-price periods are sometimes left out anyway and therefore do not contribute as much to the resulting profits as in the simple scenario. Nevertheless, by completely leaving out these periods, annual profits decrease to S$ 0 to S$ 25 for reserve and S$ 71 to S$ 90 for regulation, respectively, again depending on the applied mobility pattern. Concluding from the results, profits in this configuration might not be high enough to practically apply the V2G concept.

8.4.4 Sensitivity Analysis

As discussed in Sect. 8.3, V2G profits strongly depend on multiple parameters. Above all are the battery inherent variable depreciation costs, the energy efficiency, and the electricity market prices whose influence will be discussed in this section. All investigations in this section are based on the simple scenario introduced in Sect. 8.4.3. Analyses are done ceteris paribus, meaning that each section discusses the variation of only one specific parameter.

8.4.4.1 Battery Model

The simplest view on battery lifetime which has been broadly employed in V2G literature is to assume a fixed number of possible cycles. Using this approach, battery lifetimes between 1,000 and 6,000 cycles would yield annual profits in the range between S$ 343 and S$ 2,992 in the presented case. While any of these cycle stabilities may be theoretically achievable under specific conditions, fixing the number of possible cycles to one particular value is a completely arbitrary decision because it neglects the dynamic processes within the battery. To realistically assess profits, a proper battery aging model is of utmost importance. A battery aging model provides the battery inherent variable depreciation costs from charging and

Table 8.4 Profits depending on the battery model

Battery model	Cyclic lifetime/Depending variables	Profits [S$/year]
Static	1,000	343
	2,000	785
	3,000	1,238
	4,000	1,736
	5,000	2,322
	6,000	2,992
Non-linear	DOD	653
	DOD, SOC	394

dispatching and is the main factor influencing the magnitude of annual profits. As described in Sect. 8.3.2 the cycle stability highly depends on a large number of parameters and varies among different cell chemistries.

In [20], a battery model for V2G profit calculation is presented that accounts for the important dependency of battery lifetime from the DOD. This model provides a significantly more realistic representation of battery aging costs than assuming a constant cyclic lifetime, however, it still lacks the SOC as the second most important parameter. Section 8.3.2 refers to a refined battery model that incorporates both, DOD and SOC, as parameters for the cyclic lifetime of a battery. This model more realistically assesses battery depreciation costs and was used for all calculations in this case study except stated otherwise. Results obtained by using the simpler model from [20] indicate annual profits of about S$ 650 while incorporating the SOC dependency reduces annual profits to roughly S$ 400. The significant discrepancies to the static approach and even between the fairly realistic models thus demonstrate that for any estimation of V2G profitability, a careful choice for a proper battery model needs to be made. Annual profits achievable depending on different battery models are presented in Table 8.4 (Fig. 8.6).

Varying the initial price of the battery pack has the same effect on the variable costs as proportionally changing the cyclic lifetime. Cutting fixed battery pack costs in half thus results in the same profits as doubling the cyclic lifetime. PEV manufacturers are already pre-selling battery packs to be delivered in 8 years at a price four times lower than the current one.[2] Besides the proper choice for the battery model, the initial battery pack costs are therefore a crucial factor when re-investigating V2G in the future.

8.4.4.2 Efficiency Factor

With the increasing maturity of battery technology or the integration of super capacitors into PEVs, the charging/discharging efficiency is expected to undergo

[2] http://www.teslamotors.com/blog/2013-model-s-price-increase.

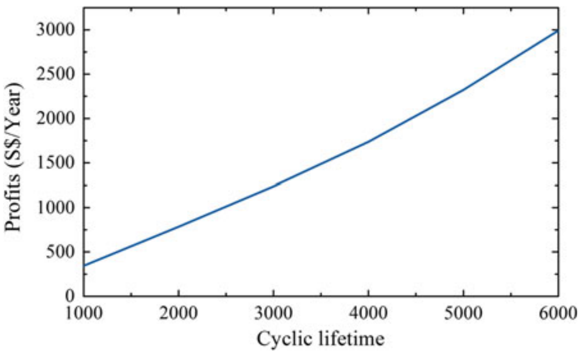


Fig. 8.6 Profits as a function of the cyclic lifetime

further improvements. The reduced energy dissipation will therefore result in decreased variable costs and ultimately in an increase in profits per period. Analysis show that on an absolute value in the range from 0.80 to 0.90, annual profits increase by roughly S$ 8 with a 1 % increase in efficiency. This relation results in a 15 % increase of annual profits when increasing the efficiency in the given range by 10 %. This relation is presented in Table 8.5 and Fig. 8.7 respectively. The impact of the efficiency factor is therefore slightly higher than proportional but cannot be considered a game changing parameter with regard to V2G profits.

8.4.4.3 Market Prices

Although prices are fixed by the electricity market, it might be useful to understand their influence on the profit. For this purpose, the end-consumer price for electricity (ET), the energy payment (USEP), as well as the capacity payment (MFP) were altered. As shown in Table 8.6, an increase/decrease in the ET by a factor will result in a decrease/increase of profits by less/more than this factor. For the USEP and the MFP it is the opposite case, meaning an increase/decrease in the USEP or MFP by a factor will result in an increase/decrease of profits by more/less than this factor. The ratio of

Table 8.5 Profits depending on the efficiency factor

Efficiency (one-way)	Efficiency (two-way)	Profits [S$/year]
0.7	0.49	207
0.75	0.56	248
0.8	0.64	293
0.85	0.72	343
0.9	0.81	396
0.95	0.9	468
1	1	565
0.89	0.80	394

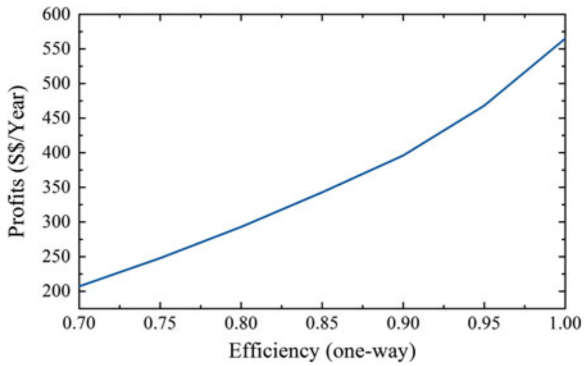


Fig. 8.7 Profits as a function of the efficiency factor

Table 8.6 Profits when varying the ET, USEP and MFP

Price	Price factor	Profits [S$/year]
ET	0.5	1,062
	0.75	565
	1	394
	1.25	324
	1.5	279
MFP	0.5	121
	0.75	233
	1	394
	1.25	639
	1.5	1,025
USEP	0.5	248
	0.75	310
	1	394
	1.25	542
	1.5	858

those factors favors the USEP and the MFP over the ET. An increase of the ET may therefore be more than compensated by a corresponding increase of the energy or capacity payment (Fig 8.8).

In Fig. 8.9 the distribution of USEP and MFP for the whole year 2012 is shown. It can be observed that the upper 3 % of prices (Region 3) exhibit a high variance with maximum values of up to S$ 4,000 in case of the USEP. This domain is followed by a broad plateau which consists of about 83 % of all time periods (Region 2). Finally, 14 % of the time intervals exhibit low prices with again higher fluctuations (Region 1). As already pointed out in Sect. 8.4.3, periods of Region 3 represent the extraordinarily profitable periods. In case of a low value of a parameter with a positive influence on profits (e.g., efficiency), only the periods of Region 3 are profitable. By increasing the value of this parameter, the intervals

Fig. 8.8 Profits as a function of the ET, MFP and USEP

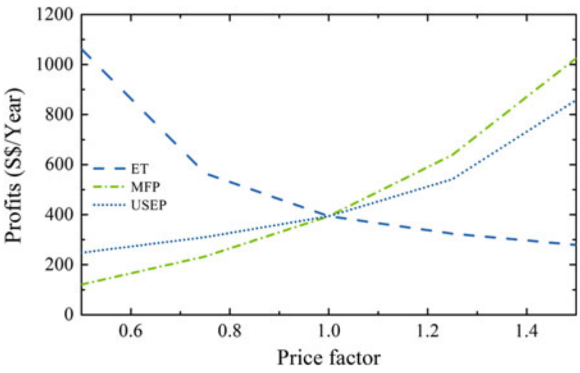
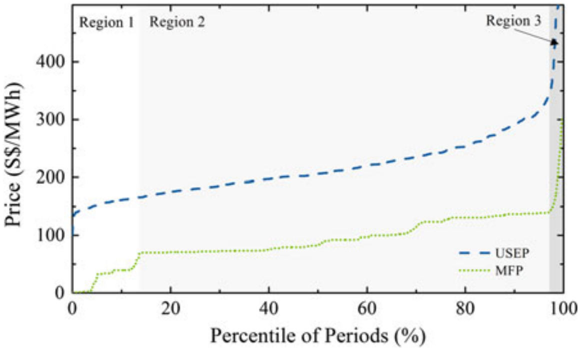


Fig. 8.9 Distribution of USEP and MFP



belonging to the plateau of Region 2 also become economically viable. Once this area is reached, a slight increase in this parameter significantly raises the number of profitable time periods leading to a considerable profit increase.

8.5 Discussion

This section summarizes and evaluates the findings of applying the presented intelligent agent behavior model to the electricity market data of Singapore. To show the relevance of these results for other countries, a qualitative discussion of the characteristics of the Singaporean market compared to other national markets is given. Furthermore, the benefits of the proposed strategy on power grid stability as well as the limitations of the applied cost and revenue model are examined. Finally, advantageous conditions for the practical implementation of the V2G concept are discussed.

8.5.1 Profitability of V2G in Singapore

The results presented in Sect. 8.4 show that given present market conditions of Singapore and realistic technical parameters, a maximum annual profit of S$ 110 could be achieved at the regulation market. This value, however, is only valid when the PEV is continuously grid-connected at all times except for the dozen outlier periods. When investigating the more realistic mobility pattern based scenario with a lower PEV availability profits decrease to S$ 80 per year. Since these numbers are the outcome of an optimization specifically targeted on profits, it is clear that alternative approaches would yield lower annual incomes. This shows that an economically motivated optimization strategy is a necessary condition for making V2G profitable in practice.

Nevertheless, these values indicate that under the given conditions V2G is yet unlikely to be an attractive concept for PEV owners in Singapore. There are, however, three main factors which could increase profits and thereby create conditions under which V2G could become a profitable business case. The first aspect relates to the battery where further development may either lead to reduced investment costs or where advancements in cell chemistry could yield higher cyclic lifetimes. This is, however, unlikely to happen on very short time scales. A second more realistic scenario to increase profits is therefore to utilize more information on future prices in the optimization process. Since longer temporal lookaheads also come with a higher uncertainty, this would, however, require improvements of the optimization approach to efficiently deal with uncertain information. A third factor could be to give a higher weight to capacity payments. In this study it was assumed that all energy offered to the ancillary service market is also being dispatched. In practice it could, however, also be possible to only receive a capacity payment without actually delivering energy. In this case, no depreciation costs occur which would ultimately have a positive effect on profits. Summing up all chances of realistically increasing profits, PEV owners may then be able to achieve an additional income of a few hundred S$ per year.

8.5.2 Applicability to Other National Markets

The cost-revenue model, the battery model, and the optimization method are generic under the described conditions and can be equally applied to other markets. In contrast, the results of the case study are specific to the conditions of Singapore and would not necessarily be identical in other markets. A quantitative conclusion for V2G in other countries would therefore require other case studies building on the presented models. Hence, in this section only a qualitative discussion putting the results obtained for Singapore into a greater context can be provided.

In the NEMS, as in many other markets, there is an energy and a capacity payment. Especially the latter has been identified as a major source of profits [2, 10, 13].

Economic analyses have to show whether or not the abolishment of this revenue stream in certain countries like Germany can be compensated by a higher energy payment. To investigate these questions, no changes in the cost-revenue model and the presented optimization method are required.

In Singapore, the fiscal framework appears to be advantageous in regard to the economic viability of V2G. The end-consumer electricity price almost entirely consists of generation and transmission costs without much taxes added. This is in contrast to other markets where a PEV owner would have to pay consumption taxes on the electricity price even if the energy may just be bought for the purpose of feeding it back into the grid. A different taxation policy could therefore yield higher profits in these countries while there is little potential for improvements in Singapore.

8.5.3 Model Limitations

A remaining weakness of the optimization approach is the inability to deal with uncertain price information and to make improved predictions based on knowledge from the past. This limits the temporal lookahead and therefore leaves parts of the optimization potential unutilized. This deficiency can, however, be addressed by further elaborating the optimization algorithm to incorporate these aspects.

Another issue is the difficulty of determining battery depreciation costs. As discussed above, this work employs empirically validated battery models which are believed to give a good estimation of battery aging costs. Nevertheless, conducting measurements regarding cell aging is time consuming and results in battery models that are always one generation behind the cells implemented in newest PEVs. The discussion in Sect. 8.3.2 also shows that the aging process depends on a large variety of parameters and may significantly differ among various cell chemistries. It therefore needs to be considered that for application purposes, battery aging models specifically developed for the corresponding battery type need to be employed.

8.6 Conclusion and Outlook

In this chapter, it is argued that static approaches for assessing the economic viability of V2G are of only limited informative value because market dynamics are neglected and the optimization potential individual agents have remains unexploited. In contrast, models which take the dynamics of market prices into account to optimize the charging/dispatching strategy for each individual PEV are considered more suitable for showing the economic potential of the V2G concept. Using dynamic approaches based on real-time information, a PEV may autonomously decide on its individual charging/dispatching strategy. This is achieved by the introduced optimization model which dynamically adapts charging/dispatching power of a PEV in each time period depending on its internal cost function and externally given market prices.

From the discussion of the results, it becomes clear that a control strategy motivated by an economic optimization approach is a necessary condition for the realization of the V2G concept in practice. Above all, this requires that V2G participants gain access to dynamic market prices for electricity instead of being bound to fixed tariffs. This is also necessary to trigger the behavior of V2G providers in order to achieve an effective load curve flattening. Current profits are assumed to be at the lower range of what PEV owners would accept for providing their batteries for ancillary services. An increase of prices for regulation and reserve energy which may follow growing shares of renewable energy sources or the introduction of premium tariff rates for V2G power would therefore be beneficial for the introduction of the V2G concept. On the cost side, battery depreciation is a crucial factor for the economic viability of V2G. While only moderate improvements of cyclic stabilities are expected in the near future, battery purchase costs are assumed to undergo a more rapid decrease, which in turn would lead to a significant cost reduction of V2G. A game changing innovation could additionally be the introduction of supercapacitors which exhibit significantly higher cyclic stabilities than batteries.

A possible soft factor obstructing the acceptance of the V2G concept is the reluctance of PEV owners to assign control of their vehicle battery to a third party. The possibility to manually take over control of the charging process by means of a smart mobile device could therefore be helpful for creating appropriate framework conditions for the practical employment of V2G.

A next step towards the implementation of V2G is to extend the optimization algorithms to address the issue of uncertain price information. By also incorporating machine learning mechanisms to improve price prediction, this can boost further exploitation of the optimization potential. Another important aspect of a feasible system in practice is the implementation of an aggregator. The challenge faced by this entity is to synchronize charging and discharging operations of a large number of PEVs under individual constraints. For this purpose, an algorithm has to be developed which estimates a VPPs power generation capacity and triggers behavior changes of the involved PEVs in case the power dispatch obligations cannot be fulfilled. Building on the entity of individual optimization algorithms combined with an aggregator mechanism would allow simulating the entire system in a nanoscopic simulation environment to quantify the overall impact on power grid stability. Together with temporally resolved data on the required quantity of regulation and reserve energy, this could then also yield a sound estimation of the V2G market size.

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