International Journal of Sustainable Energy Planning and Management Vol. 07 2015 71-78

International Journal of
Sustainable Energy Planning and Management

Strategies for Charging Electric Vehicles in the Electricity Market

Nina Juul[1a], Giovanni Pantuso[a], Jan Emil Banning Iversen[b] and Trine Krogh Boomsma[c]

[a] *DTU Management Engineering, Technical University of Denmark, P.O. Box 49, 4000 Roskilde, Denmark.*
[b] *DTU Compute, Technical University of Denmark, Matematiktorvet, 2800 Kgs. Lyngby, Denmark.*
[c] *Department of Mathematical Sciences, University of Copenhagen, Universitetsparken 5, 2100 Copenhagen East, Denmark.*

ABSTRACT

This paper analyses di erent charging strategies for a fleet of electric vehicles. Along with increasing the realism of the strategies, the opportunity for acting on the regulating market is also included. We test the value of a vehicle owner that can choose when and how to charge; by presenting a model of four alternative charging strategies. We think of them as increasing in sophistication from dumb via delayed to deterministic and stochastic model-based charging. We show that 29% of the total savings from dumb are due to delayed charging and that substantial additional gains come charging optimally in response to predicted spot prices, and in some settings additional gains from using the up and down regulating prices. Particularly, strategies are chosen from uncontrolled charging through deterministic optimization, to modelling the charging and bidding problem with stochastic programming. We show that all vehicle owners will benefit from acting more intelligently on the energy market. Furthermore, the high value of the stochastic solution shows that, in case the regulating price differs from the expected, the solution to the deterministic problem becomes infeasible.

Keywords:

Electric vehicles,
Regulating market,
Stochastic programming,
Bidding.
URL:
dx.doi.org/10.5278/ijsepm.2015.7.6

1. Introduction

Increased focus on electrified transportation has an influence on power systems. Charging and discharging of electric vehicles (EVs) could help power plants to produce in a more steady pace, even though an increased amount of fluctuating renewables are infuencing the system. Fortunately, optimising the charging from the power system point of view often corresponds to optimising from the vehicle owners point of view. Hence, charging when experiencing high amount of free power producing capacity and prices are low and stop charging when low amount of free power producing capacity and prices are high. With an expected increase in EV penetration, we investigate the benefits of entering the market and charging intelligently in response to market prices.

From the vehicle owners' point of view, optimising the charging might include participating in the regulating market, hence, bidding capacities for up- and down regulation. This requires enough battery capacity left for either up- or down regulation, and, thus, has an influence on the planned charging at spot price. However, when planning the charging of the vehicle, the regulating prices are unknown and stochastic. We envision a vehicle aggregator that can place bids for a large group of vehicles. An aggregator can be compared to a cell phone company, monitoring and charging for the communication on the phone. These companies have

[1]Corresponding author e-mail: njua@dtu.dk

a large amount of customers as would the aggregators. The aggregator would bid for himself, however, the benefit or at least some of it, will go to the vehicle owner, e.g. in terms of an availability bonus. For simplicity, we present our model for one vehicle only.

Optimal bidding into the electricity market has been the focus of many articles. Within the field of mathematical programming, [4] focuses on optimal sequential bidding in both the day-ahead market and regulating market, considering uncertainty in regulating prices. Other examples of bidding models are [8, 16]. These models are all considering price-taking electricity producers and include details such as start-up costs, ramping restrictions, and storage balances.

The charging of electric vehicles (EVs) has been a focus area for a considerable number of articles. This diverges from the challenges and benefits in the entire energy system [12, 17] to optimal charging when driving patterns are stochastic, e.g. [11]. In [15], a deterministic model has been developed, showing incentives for flexible charging. They have clustered the vehicles depending on driving patterns, and show how optimal charging primarily fills the valleys of electricity demand.

A few of the articles have focused on the electric vehicles bidding in the power market. In [2], a deterministic model with hourly time steps has been used to optimise bidding on both the day-ahead market and for secondary reserves. [6] provides a dynamic approach to the bidding problem, focusing on regulating reserves only. Here, the bidding is split into two time periods; day 8-20 and night 20-8, and each bid counts for an entire period. Furthermore, they argue that large vehicle pools compensate for the stochastic variation.

Stochastic programming has been used by [14, 1, 19, 9]. [14] maximizes the revenue to the aggregator in a two stage model, where bids are placed in the first stage and realised in the second. No discharging is allowed and the day-ahead market is not included. Another two stage model is developed in [1], where they mitigate risk by coordinating bids on day-ahead market between wind power, thermal power, and electric vehicles. Thereby, they try to minimise the trading risks from market and wind uncertainties. [19] also focus on two-stage problems, where they focus on bidding in both markets simultaneously and bidding in the day-ahead market only followed by participation on the regulating market. For regulating market only, they use rolling planning, hence, a series of two stage problems, to optimise for each hour of the day. The principle of rolling planning has been extended in [9] by using a multi-stage model, maximising probability that the regulation bid is accepted. The focus is on plug-in hybrid vehicles, resulting in the vehicles being able to drive even though, the charging does not meet the target.

The contribution of this paper is to evaluate the benefit of more sophisticated charging strategies for the EV and whether the different types of vehicle owners can benefit from participating on the regulating market. Four different charging strategies are compared, including deterministic and stochastic modelling. We allow for both up and down regulation in terms of either charging when not planned (down-regulation) and stopping a planned charging (up-regulation). Hence, we do not allow for discharging of the vehicles.

The article is structured as follows. Next section introduces the market used in the model as well as the charging schemes. Section 3 describes the model and section 4 the case study. In section 5, the results are presented. Section 6 discusses the approach and section 7 concludes.

2. Market and charging

In the modelling, we focus on energy markets similar to the Nordic European countries, Norway, Sweden, and Denmark. We include both the spot market and the regulating market. The day-ahead market, also known as the spot market, is the market for trading power for delivery the coming day. The regulating market is a market for balancing the difference between the planned production and the actual demand. Trading is done one hour before delivery [18]. We assume market prices can be forecasted with sufficient precision at the time of bidding, and simplify the model to capture the new information obtained between day-ahead and intra-day trading.

We assume that the spot price is known when planning the charging on this market. However, the regulation prices are unknown and uncertain. Hence, we are aiming to see if the increased details in modelling and also the ability to bid on the regulating market will create a value for the vehicle owners-either by bidding themselves (we are aware that this might not be a possibility, due to minimum bid sizes) or by having an aggregator controlling a fleet of vehicle bidding into the regulating market (also called the intra-day market). According to energinet.dk [7], bid sizes are required to be between 10 MW and 50 MW. This would call for a parked fleet of approx. 1450 EVs. However, assuming vehicle charging has no influence on prices, our results scale to a number of vehicles. Our modelling allows us to analyse the contribution of the single vehicles and, thus, the benefits of different combinations of vehicles for an aggregator.

When discussing up-regulation, we believe that it is questionable whether the vehicle should be able to actually discharge. However, a great deal of the up-regulation could come from not charging when planned, hence, giving back the amount not charged yet to the power system (see [12]). For computational tractability, we confine ourselves to a linear representation of the interactions between charging and the grid.

Furthermore, we assume that the vehicles are always plugged in when parked. This might be too optimistic and, hence, create too much flexibility. However, when owning a fleet, this often does not create a problem, because some of the vehicles will be plugged at each time period. We will consider this when interpreting the results.

For analysing the value of information, a number of charging strategies are analysed. We are comparing the following charging strategies:

- *Uncontrolled charging* In uncontrolled or 'dumb' charging, we assume that the EVs charge their batteries as soon as they are plugged in to the electricity grid, hence, as soon as they return from a trip. Furthermore, we assume that they always fill their batteries the same amount as they have discharged while driving, to keep the battery full and be ready for the next trip. Hence, no information except the driving pattern is needed for this type of charging. Furthermore, this strategy means that the vehicle owner will not act on the regulating market.
- *Delayed charging* As with uncontrolled charging. However, the charging is delayed from when the EVs are plugged in. In this situation, some kind of intelligence is needed, in order to delay the charge, e.g. a timer setting the time for the charge to begin. However, still no actions can be taken on the regulating market.
- *Deterministic charging* The EVs optimise their charging based on deterministic future electricity prices. We optimise the EV charging based on a forecast of future market prices on the regulating market. The forecast is based on historical data of, e.g. a 1 year period. Price variations are, over a longer period, assumed to be similar, thus, a charging strategy based on these could add further value to the vehicle owner. Hence, in this situation the vehicle owners can place bids on the regulating market, increasing the value of the EV. It is assumed that the vehicle owners can act both on the up- and down-regulating market. However, up-regulation can only be done in terms of stopping or downscaling already planned demand, hence, no discharging of the vehicles are performed.
- *Stochastic charging* As with the deterministic charging, the EVs optimise their charging based on expected future electricity prices. However, here the market prices on the regulating market are considered uncertain, and, thus, they will be based on probabilities of future prices going up or down. This is done, using a two stage stochastic optimisation model. A number of scenarios will be developed to represent different possible price realizations. Charging decisions are made before realising the actual regulating price. Here, we are increasing the details of information in terms of the variation in historical price developments. This will be based on stochastic optimisation and as with the deterministic model, this enables bidding on the regulating market.

Our hypothesis is that increasing the details in the modelling the charging decisions will also increase the benefits for the vehicle owner and decrease the costs of electricity. However, the question is to which extend and, hence, how advanced the decision support system needs to be for the vehicle owner to benefit from these. Furthermore, the extent to which the vehicle owner can play an active role in the power system with benefits is also expected to increase with increased information.

3. Modelling description

In the following, we are assuming the vehicle owner is a price taker. We are focusing on one operation day, namely a 24–hour time period. This will be divided into 24 time steps, where $t = 1$ represents the first hour, thus, the one between 00:00 and 01:00. $t = 0$ represents the time period before the calculation period.

3.1. Uncontrolled charging

The charging after each trip can be calculated using the following formula.

$$Ch_t = min\left\{Ch^{max}; \sum_{k=t-\tau-\mu}^{t-\mu} Dr_k - \eta. \sum_{k=t-\mu}^{t-1} Ch_k\right\} \quad (1)$$

Where, Ch_t is the planned charging at time t in the spot market, Ch^{max} is the maximum charging within each time step, and Dr_t is the driving at time t. τ is the length of the trip, μ is the number of time steps the vehicle has been charging continuously, and η is the charging efficiency. The equation reflects the fact that if the vehicle has used more power on the trip than can be charged within the first hour due to grid connection, the charging continues in the next hours, until fully charged.

Based on the above, the costs can be calculated by;

$$Z = \sum_{T=1}^{T} P_t^{spot} Ch_t \quad (2)$$

Where P_t^{spot} is the spot price.

3.2. Delayed charging

As with uncontrolled charging, this can be calculated by multiplying spot price and charging. We are assuming that the vehicles are charging at night, whenever possible. Now, the charging equation will be;

$$Ch_t = \min\left\{Ch^{\max}; \sum_{k=t-24-\mu}^{t-\mu} Dr_k - \eta \sum_{k=t-\mu}^{t-1} Ch_k\right\} \quad (3)$$

Hence, the driving from the past 24 hours is summed, and the vehicle is charged to be able to meet the next 24 hours. This equation hold from the starting time, e.g. midnight, and until the vehicle is fully charged. Then the charging starts over 24 hours later, e.g. at midnight.

3.3. Deterministic charging

For deterministic charging, we are minimising the costs of charging the vehicles.

$$\min z = \sum_{t=1}^{T}\left(P_t^{spot} Ch_t + \left(PE_t^{down}\lambda_t^{down} - PE_t^{up}\lambda_t^{up}\right)\right) \quad (4)$$

Where PE_t^{up} and PE_t^{down} are the expected up and down regulation prices respectively. λ_t^{up} and λ_t^{down} up is the charging in the regulating market.

Storage, St_t, is balanced in each time period in order to meet restrictions on storage capacity as well as the need for driving:

$$\begin{aligned} &St_t = St_{t-1} + \eta \cdot Ch_t + \eta \cdot \lambda_t^{down} - \eta \cdot \lambda_t^{up} - Dr_{t,} \forall t = 1,...,T \\ &St^{\min} \le St_t \le St^{\max}, t = 1,...,T \end{aligned} \quad (5)$$

Charging has to be within the grid capacities;

$$Ch_t \le Ch^{\max} \quad (6)$$

Furthermore, restrictions are made in order to ensure, that driving and charging cannot happen at the same time.

$$\begin{aligned} &Ch_t\, Dr_t = 0,\; t = 1,...,T \\ &\lambda_t^{up}\, Dr_t = 0,\; t = 1,...,T \\ &\lambda_t^{down}\, Dr_t = 0,\; t = 1,...,T \end{aligned} \quad (7)$$

Because of the assumed up-regulation not being an actual discharge of the battery, also need to ensure that the charging is always greater than λ_t^{up}.

$$Ch_t - \lambda_t^{up} \ge 0,\;\; t = 1,...,T \quad (8)$$

And finally, we have the non-negativity constraints:

$$St_t, Ch_t, \lambda_t^{up}\lambda_t^{down} \ge 0,\;\; t = 1,...,T \quad (9)$$

3.4. Stochastic charging

In stochastic charging, the regulating prices are uncertain. Compared to the deterministic model, we have introduced the scenarios, s, and probabilities for each scenario to be realised, π_s, in the stochastic model. The deterministic equivalent to the stochastic program is:

$$\begin{aligned} &\min z = \sum_{t=1}^{T}\left(P_t^{spot}(Ch_t) + \sum_{s=1}^{S}\pi_s\left(PE_{t,s}^{down}\;\lambda_{t,s}^{down} - PE_{t,s}^{up}\;\lambda_{t,s}^{up}\right)\right) \\ &s.t.\; St_{t,s} = St_{t-1,s} + \eta Ch_t + \eta\lambda_{t,s}^{down} - \eta\lambda_{t,s}^{up} - Dr_t, \\ &\forall t = 1,...,T, s = 1,...,S \\ &\quad St^{\min} \le St_{t,s} \le St^{\max}, t = 1,...,T, s = 1,...,S \\ &\quad Ch_t \le Ch^{\max},\;\; t = 1,...,T \\ &\quad Ch_t\; Dr_t = 0,\;\; t = 1,...,T \\ &\quad \lambda_{t,s}^{up}\; Dr_t = 0,\;\; t = 1,...,T,\;\; s = 1,...,S \\ &\quad \lambda_{t,s}^{down}\; Dr_t = 0,\;\; t = 1,...,T,\;\; s = 1,...,S \\ &\quad Ch_t - \lambda_{t,s}^{up} \ge 0,\;\; t = 1,...,T,\;\; s = 1,...,S \\ &\quad St_{t,s}, \lambda_{t,s}^{up}, \lambda_{t,s}^{down} \ge 0,\;\; t = 1,...,T,\;\; s = 1,...,S \\ &\quad Ch_t \ge 0,\;\; t = 1,...,T \end{aligned} \quad (10)$$

Furthermore, we have introduced a constraint saying that you cannot provide up regulation if down regulation is needed and vice versa. This was needed, since in some cases it could pay off to plan charging and then provide up-regulation in these hours later - even though some scenarios were generating worse prices.

As can be seen from the model, the second stage decision (the up and down regulation) is decided upon based on a span of future regulating prices, and the first stage decision, hence the charging in the spot market, is based on the specific realization of up and down regulation. Scenario generation will be described in section 4.4.

4. Case study

Our case study focuses on one vehicle type, namely Nissan Leaf. Specifications are given in Table 1. Nissan Leaf has two different battery use settings; long distance using the battery 100% or long life using the battery 80% [10]. We are using the long distance and, hence, assuming that 100% of the battery is available for driving and charging. However, in our analyses, the battery is never depleted below 20%. Thus, we might as well use the long life.

4.1. Data and assumptions

We are assuming the vehicles are plugged to the electricity grid whenever they are parked. Each vehicle have an assumed connection with 3 phases 10 Amps, resulting in a grid connection capacity of 6.9 kW. Hence, maximum charging capacity in each hour is 6.9 kWh. Furthermore, we have assumed a charging efficiency of 0.9.

4.2. Driving patterns

We use the clustered driving patterns found in [15]. All 20 patterns are included in order to get an idea whether there are driving patterns or life styles where more sophisticated modelling is of greater value. This way we can also analyse whether it is more beneficial to own a fleet of vehicles with different driving patterns or a fleet with the same driving patterns.

Table 1: Based on ([5])

Parameter	unit	value
Battery capacity	kWh	24
Efficiency	km/kWh	5.8
Total charging time	hours	6–7
Max driving per charge	km	199

4.3. Spot prices

For our analyses, we have used historical hourly spot prices from four days in four different seasons in 2014, hence, January 1^{st}, April 1^{st}, July 1^{st}, and October 1^{st}.

4.4. Regulation prices

Forecasting differs for the different analyses. No forecasting is needed for uncontrolled and delayed charging. For the deterministic model, we are using an average of the price deviation from spot to regulation prices on an hourly basis, based on data from year 2013. This corresponds to the average of the scenarios for the stochastic analysis. Hence, the regulating price is calculated based on the spot price plus/minus the deviation, depending on whether it is up or down regulation.

4.4.1. Scenario generation

Scenarios are based on data from year 2013. Regulation price scenarios are generated by means of the heuristic method described in [13]. The regulation price at each hour of the day is modelled as an independent random variable. The method uses marginal distributions for the random variables and copulas to describe the dependence between the marginal distributions. Marginal distributions and copulas have been estimated based on historical regulation prices.

5. Results

Results show decreasing costs with increasing intelligence in the charging decision. Figure 1 shows the total costs of charging the 20 different vehicle

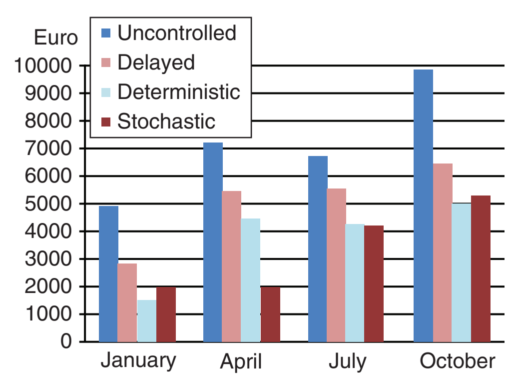

Figure 1: Total costs for different charging schemes.

types (one of each). As seen from the figure, a large decrease is experienced between uncontrolled and delayed charging, hence, only moving charging to the night time. However, another large decrease can be found using either deterministic or stochastic modelling, especially with the electricity prices in the April data.

As for the gain of using stochastic modelling instead of deterministic, we use the value of the stochastic solution (VSS) described in [3].

However, when we try to solve the stochastic problem using the first stage solution of the deterministic, the problem becomes infeasible. This has been tried both with the implemented scenarios and another set of scenarios. Infeasibility of $E[z(x^*, \xi)]$ is equivalent to a very high VSS. Hence, the solution to the deterministic problem is not robust towards slight changes in the regulation prices and, thus, regulation possibilities.

This lack of robustness is partially due to some inappropriate planning on the up-regulation side. If we try to remove the possibility of up-regulation, we get the following VSS for the total of all 20 vehicle types:

January	9.762 €
April	613.594 €
July	584.433 €
October	145.585 €

The rather high values for April and July, is because the stochastic solution only charges the vehicles on the regulating market. Hence, we count on the need for enough down regulation at some point during the day, when the car is parked. Looking at the charging pattern as well as up and down regulation, it is evident that almost all of it is in the night time. Hence, most of the vehicles will be parked and the assumption that vehicles are plugged in when not driving, does not influence our results much if at all.

In Figure 2, we see the cost average from the four seasons using the different clusters of driving patterns. From the figure we can see that we experience a decrease in costs between 40-60% when using the stochastic solution. Furthermore, focusing on Figure 3 we see that the monetary saving is quite different for the

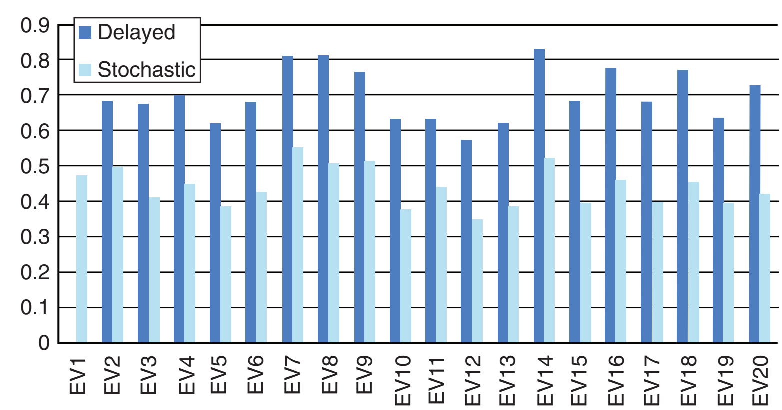

Figure 2: Average costs as percentage of cost of uncontrolled charging.

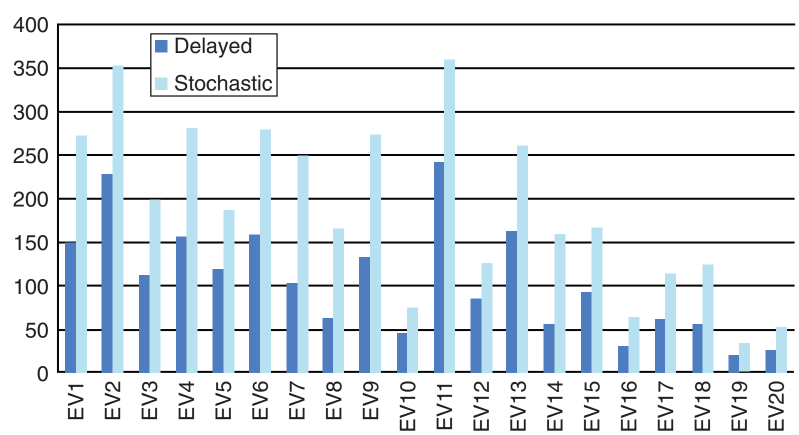

Figure 3: Average costs savings €.

different vehicle types - both because of the different charging needs, but also due to the different timing opportunities for charging.

Based on these analyses, we see that the savings for vehicle types EV10, EV16, EV19, and EV20 are very low. If an aggregator only has these vehicle groups in his fleet, the increment to act smart on the regulating market is a lot smaller than with a fleet of, e.g. EV11.

6. Discussion

From the results we see that in general it is of great value to introduce a stochastic model to optimise the charging and bidding on the regulation market for electric vehicles. The results could be scaled to a large number of vehicles, imitating that of an aggregator. However, we need to keep in mind that an increased number of vehicles does not increase the expected savings proportionally. The regulating market only needs a certain amount of regulating power. However, having a diversified fleet could enable bidding into the market at most hours, increasing the expected earnings.

The model developed in this article could be enhanced to either include rolling planning for more details, or to develop a multi-stage stochastic model. Hereby, the value of more sophisticated modelling could be studied as well as to which extend it is still beneficial to increase the details.

Furthermore, one could argue that normally reserves are not needed in the same direction throughout the complete hour. However, the intra-day market works on an hourly basis, but often does not allow for us to, e.g. provide down regulation services for the complete hour. Adjusting the modelling to take the uncertainty of the amount of power to be available for regulation could therefore, also be a subject of further research. Finally, other devices in the power system can also provide the same kind of demand response as the EVs and could easily benefit from the detailed modelling as well. It could, e.g. be interesting to look into the values for electric heating, electric boilers, and electric cooling.

7. Conclusion

Using mathematical models for charging the electric vehicles adds value to the vehicle owners or aggregators. The value varies between the different uses of the vehicles, for some the value is large, for others, the planning most likely does not give a value great enough for one actor to consider pooling with others and implementing the necessary intelligence in the vehicle. Results show decreasing costs with increasing sophistication in the models. The increase going from uncontrolled to delayed charging is expected due to the lower power prices at night. Hence, the vehicle owners can benefit from delayed charging. Moving further to deterministic charging, gives another benefit, primarily found in the good price windows for up- and down regulation. However, we have to keep in mind, that not all these prices windows are an option in the sense that what seems a good up regulation price window could turn out to be only a down regulation possibility and vice versa. Moving further to the stochastic charging strategy, a slight benefit is seen compared to the deterministic model. The reason that the stochastic strategy seems only slightly better than the deterministic is that many of the good price windows are hard to predict, and hence, the good benefits we saw in the deterministic case are likely not as good as they seemed.

We have showed, that for acting on the regulating market, the value of a stochastic model over a deterministic model is very high (with an infeasible stochastic solution to the deterministic first stage). Only focusing on the day-ahead market with possibilities for down regulation, also results in a rather large VSS. Moving on to more detailed stochastic models might increase the value even further.

Acknowledgements

This article is part of the ENSYMORA project funded by the Danish strategic research council.

References

[1] Al-Awami AT, Sortomme E, Coordinating Vehicle-to-Grid Services With Energy Trading, IEEE Transactions on smart grid 3(1)(2012), pages 453–462. *http://dx.doi.org/10.1109/TSG.2011.2167992*

[2] Bessa RJ, Matos MA, Optimization models for an EV aggregator selling secondary reserve in the electricity market, Electric Power Systems Research 106 (2014), pages 36–50. *http://dx.doi.org/10.1016/j.epsr.2013.08.006*

[3] Birge JR, Louveaux F, Introduction to stochastic programming, New York: Springer; 1997

[4] Boomsma TK, Juul N, and Fleten SE, Bidding in sequential electricity markets: The Nordic case, European Journal of Operations Research 238 (2014), pages 797–809. *http://dx.doi.org/10.1016/j.ejor.2014.04.027*

[5] Clever, *https://www.clever.dk/produkter/faa-1-krone-tilbage-pr-kwh-stroem-du-oplader elbilen-med/*

[6] Dallinger D, Krampe D, Wietschel M, Vehicle-to-grid Regulation Reserves Based on a Dynamic Simulation of

Mobility Behavior, IEEE Transactions on Smart Grids 2(2)(2011), pages 1949–3053. *http://dx.doi.org/10.1109 /TSG.2011.2131692*

[7] energinet.dk, Regulation C2: The balancing market and balance settlement, *https://www. energinet.dk/Site Collection Documents/Engelskl*

[8] Fleten SE, Kristoffersen TK, Stochastic programming for optimizing bidding strategies of a Nordic hydropower producer, European Journal of Operational Research 18(2)(2007), pages 916928. *http://dx.doi.org/ 10.1016/ j.ejor.2006.08.023*

[9] Foster JM, Caramanis MC, Energy Reserves and Clearing in Stochastic Power Markets: The Case of Plug-in-Hybrid Vehicle Battery Charging, IEEE Conference on Decision and Control (2010), pages 1037–1044. *http://dx. doi.org/10.1109/ cdc.2010.5717304*

[10] Green autoblog, http://green.autoblog.com/2013/02/21/2013-nissan-leaf-revealed-gets-75- mile-range-actually-84-in-n/

[11] Iversen JEB, Madsen H, Morales Gonzlez JM, Optimal charging of an electric vehicle using a Markov decision process, Applied Energy 123 (2014), pages 1–12. *http://dx.doi.org/10.1016/j.apenergy.2014.02.003*

[12] Juul N, Meibom P, Optimal con guration of an integrated power and transport system, Energy 36(5)(2011), pages 3523-3530. *http://dx.doi.org/10.1016/j.energy.2011.03.058*

[13] Kaut M, A copula-based heuristic for scenario generation, Computational Management Science 11(4)(2014), pages 503-516. *http://dx.doi.org/10.1007/s10287-013-0184-4*

[14] Khalid MW, Al-Awami AT, Sortomme E, Stochastic-Programming-Based Bidding Strategy for V2G Services, 4th IEEE PES Smart Grid Technologies Europe (2013), pages 1–5 *http://dx.doi.org/10.1109/isgteurope.2013.6695468*

[15] Kristoffersen TK, Capion KE, and Meibom P, Optimal charging of electric drive vehicles in a market environment, Applied Energy 88(5)(2011), pages 1940–1948. *http://dx.doi.org/10.1016/j.apenergy.2010.12.015*

[16] Ladurantaye D, de Gendreau M, and Potvin JY, Strategic bidding for price-taker hydroelectricity producers, IEEE Transactions on Power Systems 22(4)(2007), pages 21872203. *http://dx.doi.org/10.1109/TPWRS.2007.907457*

[17] Lund H, Kempton W, Integration of renewable energy into the transport and electricity sectors through V2G, Energy Policy 36(2008), pages 35783587. *http://dx.doi.org/10. 1016/j.enpol. 2008.06.007*

[18] Nord Pool spot market, *http://www.nordpoolspot.com/#/ nordic/table*

[19] Vagropoulos SI, Bakirtzis AG, Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets, IEEE Transactions on Power Systems 28(4)(2013), pages 4031–4041. *http://dx.doi.org/10.1109/TPWRS.2013.2274673*