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smart charging of electric
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Decrease of wind power balancing costs due to smart charging of electric vehicles

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Abstract—A combination of a generation planning model and a stochastic unit commitment model was used to analyze the impact of electric vehicles on power system balancing costs from the perspective of wind power. When smart charging and discharging was available, wind power balancing costs decreased by approx. 30% assuming that half of the personal vehicle fleet consisted of EVs.

Index Terms—Balancing, electric vehicles, power markets, wind power

I. NOMENCLATURE

t		set of hours
BC ₁	€/MWh	average balancing cost in the one-price system
BC ₂	€/MWh	average balancing cost in the two-price system
BP	€/MWh	real time price
WR	MWh	realized wind power production
WF	MWh	day-ahead forecasted wind power production

II. INTRODUCTION

INCREASED variation and uncertainty due to wind power will increase the power system balancing¹ costs. The costs will be largely born by wind power producers, since at large penetration levels wind power will be the main cause for balancing. The cost increase can be mitigated by the use of flexible resources that can economically integrate the variations and prediction errors in different time scales. One such option is the smart charging, and possibly discharging, of electric vehicles (EVs). Earlier work by the same authors analysed the general impacts of EVs on the power system [1], [2] and this article expands to impacts on wind power balancing costs.

The results show that EVs decrease the balancing costs of wind power and increase the share of wind power in the cost optimal power plant portfolio. Vehicle-to-Grid (V2G) has an important effect on wind power balancing costs, but most of

the benefit can be accrued from relatively small share of EVs having V2G.

EVs can increase the power system flexibility in three ways. First, with smart charging the charging would occur during the hours with low electricity prices, if possible. Second, V2G would enable discharging the batteries to the grid during hours of high prices. Third, the charging and discharging decisions can be changed when new wind and demand forecasts arrive or at the operational stage, if the system needs upward or downward regulation. There have been several articles and reports about the possible benefits from the participation of EVs in the electricity markets [1]-[19]. Studies [3], [4], [5], and [6] use historical market prices to analyze the costs and benefits of EVs and hence do not contain dynamic impact of EVs on the prices and system operation. Reports [7] and [8] analyze only the impact of immediate charging. Only few studies [1], [2], [9], [10], [18] consider that EVs can have an impact on the future generation portfolio.

Article [9] considers the effect of EVs on future generation portfolios and uses a simplified model to dispatch EVs on top of the demand profile. V2G or the use of EVs as reserves was not considered. Report [10] estimated the effect of plug-in hybrid electric vehicles (PHEVs) on future generation portfolios and report [11] analyzed how dispatch might be affected. Costs and benefits were not analyzed. Article [14] analyses the effects of PHEVs on household electricity bill based on end-user rates in combination with household scale wind power or solar PV production and thus do not have a systems perspective. Article [16] analyses the effect of smart EVs in integrating variable wind power. While the article has results on CO₂ emissions, it does not include costs and benefits. Article [18] is the only one that includes endogenous investments in transport sector as well as in power generation. However, it does not analyse the effect of EVs on wind power balancing costs. Article [19] has applied a unit commitment model to analyse the impacts of EVs. The method uses measured driving profiles and includes a piecewise approximation of depth of discharge costs. The article indicates the saturation of spinning reserve market with increasing share of EVs. The results are in line with the articles [1] and [2] by current authors.

The next section summarizes the tools and the scenarios that were used to create the results, which are presented in section IV. The article finishes with discussion in section V.

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¹ Balancing corrects most of the forecast errors that accrue after the original day-ahead forecast in demand and wind power. Intra-hour corrections are not included – it is assumed that these are in the domain of reserves.

III. METHODS AND SCENARIOS

EVs will not appear in the power system overnight without a forewarning. Their introduction, and any assumptions about that, will affect what kind of power plants will be built in the future. Smart charging EVs will exhibit a markedly different behavior from traditional consumption. They offer flexibility in the timing of the electricity consumption. Additional flexibility will promote certain types of power generation over others. As demonstrated in [2], the impact is noteworthy. The methods and scenarios have been presented in detail before [1], and are hence only summarized here.

Generation planning model Balmore was used to create generation portfolios for different EV scenarios. Balmore operates in hourly time resolution and therefore sees the variation in demand and in large-scale wind power, excluding sub-hourly variations. It assumes a perfect foresight, which means that it does not see the uncertainty in the wind power or demand forecasts. It optimizes the dispatch of generation for the whole year simultaneously and uses annualized investment costs to decide what power plants should be built in addition to existing plants in order to meet demand during every hour of the year and fulfill a yearly capacity balance requirement ensuring enough capacity to cover extreme peak load situations.

The generation portfolios from Balmore were taken to unit commitment and dispatch model WILMAR, which includes uncertainty in the form of stochastic representation of net demand. WILMAR performs a day-ahead unit commitment including demand for spinning and non-spinning reserves once per day. This includes a dispatch for the first three hours. After this, the model rolls three hours forward and receives updated forecasts. These are used to refine the original unit commitments and to dispatch the next three hours. The rolling is repeated until the next day-ahead solve is due.

The shadow prices of the intraday power balance equation are assumed to reflect the real time market prices for energy. The results on balancing costs are based on a one-price system (1). In this system forecast error is always billed according to the real time price. Another system in use is the so-called two-price system (2), where a forecast error that increases the system error pays the balancing price and a forecast error that decreases the system error receives the original day-ahead price. The WILMAR model co-optimizes the day-ahead market and the expected up and down regulation in the future balancing markets. Therefore the day-ahead market prices in the WILMAR model will not be a good representation of real day-ahead market prices, due to real electricity markets such as the Nord Pool market clearing the day-ahead market independently from the balancing markets. Hence, the two-price system balancing prices were not calculated.

$$BC_1 = \frac{\sum_t BP_t \times (WR_t - WF_t)}{\sum_t WR_t} \quad (1)$$

$$BC_2 = \frac{\sum_t \max((DP_t - BP_t) \times (WR_t - WF_t), 0)}{\sum_t WR_t} \quad (2)$$

The study assumes that all wind power errors are balanced together. In reality different actors will have independent forecast errors and are being penalized individually, hence the overall bill would be larger especially in the two-price system.

The scenarios are based on a medium size power system with a high wind power penetration. The wind penetration is a result of relatively low investment cost for wind power and it differs between the scenarios. The number of EVs was exogenously defined to present about half of the personal vehicle fleet in the example system. In the scenario ‘No EVs’, there were no EVs in the system. In ‘Dumb’ scenario the EVs started charging when they were plugged in and charged until they were full. In ‘Smart’ scenarios EVs were able to change the charging period to optimize the power system costs – within the restrictions due to vehicle use.

IV. RESULTS

The impact of EVs on cost optimal generation plant investments can be seen in Figure 1. In addition to the investments in the figure, also biomass based CHP received investments, but these changed only very little between the scenarios. In comparison to the scenario without EVs, ‘Dumb’ scenario required more flexibility (open cycle gas turbines) and more energy (nuclear and some wind). ‘Smart’ scenario required less flexibility from conventional power plants and was able to support higher share of wind power.

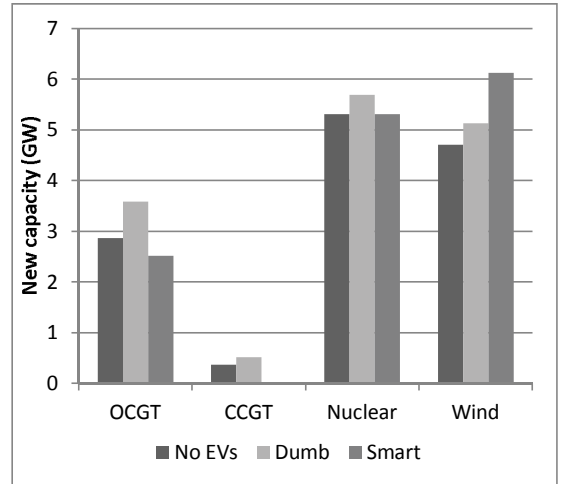


Figure 1. New investments in power generation in different EV scenarios. OCGT refers to an open cycle gas turbine and CCGT refers to a combined cycle power plant.

Figure 2 displays the wind power balancing costs in different EV scenarios calculated according to the one-price system. The balancing costs are smaller in the ‘Smart’ scenario. In comparison to ‘No EVs’ and ‘Dumb’, the flexibility of smart charging EVs decreases the real time prices. Annual balancing cost for wind power is 32% (‘No EVs’) and 41% (‘Dumb’) smaller. Electric vehicles provide balancing service at no cost, if they are able to move their

charging to another point in time. If they utilize V2G, balancing from EVs has a price due to losses (85% round trip efficiency) and variable costs (assumed to be 10 €/MWh). In 'No EVs' and 'Dumb' scenarios use of EVs for balancing is not possible and the balancing is done with more expensive power plants.

The impact of V2G on balancing costs was also tested (Figure 2). If only half of the vehicles (PHEVs in this case, hence the acronym 'V2G PHEV only'), were allowed to perform V2G, average wind power balancing cost increased by 13%. If V2G was disallowed altogether ('No V2G'), the balancing cost increased by 67% compared to the 'Smart' scenario.

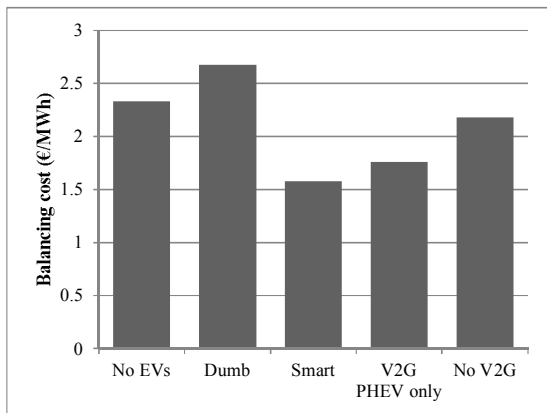


Figure 2. Wind power balancing cost in different scenarios.

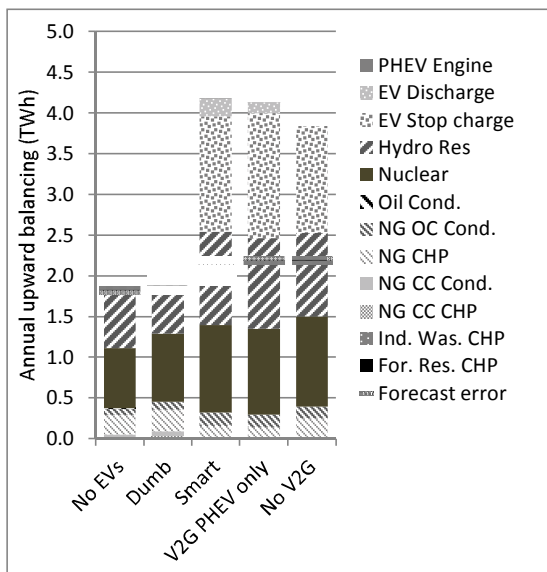


Figure 3. Sources of annual upward balancing. NG OC Cond. refers to OCGT, NG CHP refers to a combined heat and power plant using natural gas, NG CC Cond. refers to CCGT, and NG CC CHP refers to a natural gas based CHP plant using combined cycle. Ind. Was. is industrial waste and For. Res. is forest residues.

While balancing costs decrease with EVs, the amount of balancing increases considerably (Figure 3 and Figure 4). The need for balancing due to forecast errors (also in the figures) increases less: only in relation to increased wind power penetration. What happens is that the balancing with costly power plants decreases, which explains the overall cost decline in balancing. The increased balancing activity is due to transfers that optimize the system operation. The new transfers reschedule EVs to increase the full load operation of the conventional thermal fleet. This includes increased capacity factor for nuclear. Occasionally a thermal power plant can be shut down due to the transfers and this saves on fuel costs.

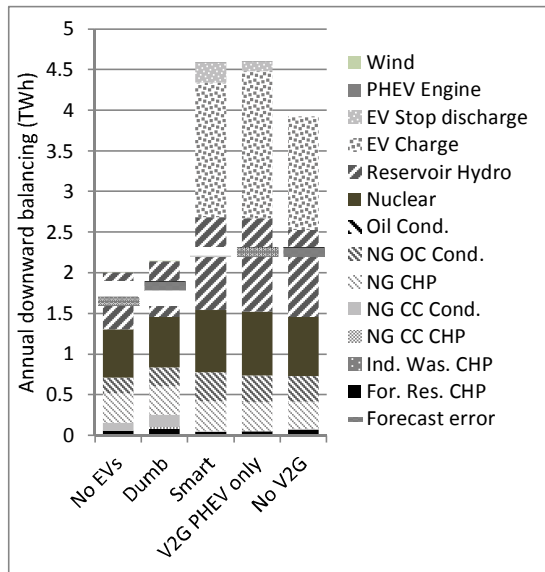


Figure 4. Sources of annual downward balancing.

Introduction of EVs will affect the real time prices and hence the revenues per MW will vary between different scenarios. Figure 5 shows revenues for wind and OCGT power plants. The revenues in scenarios with less V2G are higher in comparison to the 'Smart' scenario, since the power plant portfolios are the same and the system operation is less optimal when the EVs cannot discharge batteries to the grid, which leads to higher power prices. OCGTs receive additional revenue from fulfilling spinning reserve requirements, but this is removed when there are enough EVs to take care of this market for no cost.

Figure 6 displays the annual net profit of different power plant types using the assumed costs in the models and the market prices from the WILMAR runs. Costs include investment annuity, fixed costs, fuel costs, CO₂ price, and variable O&M costs. Revenues are from energy sales, including balancing, and procurement of spinning reserve.

OCGT has an annual net loss instead of profit. One reason for this is the capacity balance equation in Balmorel, which forces the model to build enough capacity to match the combined peak demand and reserve requirements. The investment cost of OCGT is not captured back in the

operational phase simulated by WILMAR and the result is a net loss. Highest amount of OCGT is built in the ‘Dumb’ scenario and the scenario also has the lowest net loss for OCGT – there is less competition from EVs and more net demand variability due to the inflexible charging of EVs.

Annual net loss is explained by the same rationale as for OCGTs and CCGTs, WILMAR does not include long-term marginal costs and the prices are lower due to that. Nuclear on the other hand, receives a profit during most hours since the price setters are more expensive units.

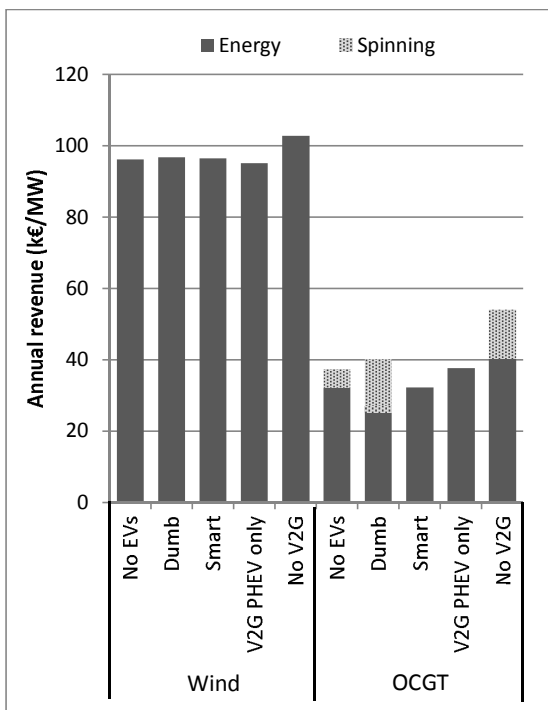


Figure 5. Annual revenue for wind and OCGT plants from real time market and provision of spinning reserves.

Balmorel approaches long-term marginal cost equilibrium in the optimization. WILMAR, on the other, optimizes according to short-term marginal (i.e. variable) costs. This means that power plants that set the peak and near peak prices will not recapture their investments costs unless scarcity pricing is present. WILMAR does not calculate scarcity prices when there is enough capacity as is the case in these scenarios. Hence, OCGTs and CCGTs are producing annual net loss in WILMAR runs. However, OCGTs and CCGTs produce more electricity in WILMAR runs than in Balmorel runs, which is a result of uncertainty in WILMAR. This does not help to capture the long-term costs, as the power prices remain too low for the price setters. OCGTs are barely getting more revenue than what are their variable operational costs. For CCGTs the margin is larger, but not nearly high enough to recapture investment annuity and fixed costs. The phenomenon is called “missing money” i.e. the inability of power plants to recover their fixed costs in electricity markets.

Annual net loss for wind remains rather stable over the different scenarios. Smart EVs will smooth price fluctuations and wind generation is experiencing a balance of price decreases and price increases in different scenarios.

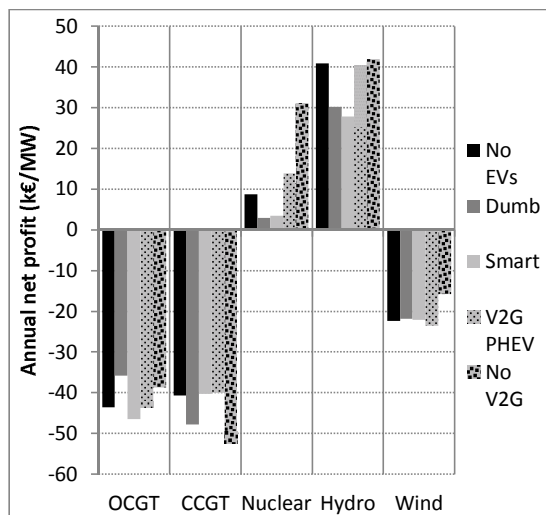


Figure 6. Annual net profit for different power plant types. To facilitate comparison, reservoir hydro power was assumed to have an investment annuity of 200 k€/MW, although it was not an investment choice.

Figures 7, 8, 9, and 10 show four days from the beginning of April. The figures show how the system copes with the largest downward balancing need during the analyzed year. Figures 7 and 8 are from the ‘Dumb’ scenario and figures 9 and 10 from the ‘Smart’ scenario. There are two major differences between the scenarios.

First, the EVs in the ‘Smart’ scenario make it feasible to schedule the thermal power plants in a more economic manner. Especially nuclear power plants are scheduled for full load operation almost all the time. The power plant portfolio has a very large share of nuclear and wind and hence this is not easy to achieve. Intraday balancing further increases the full load hours of nuclear power plants.

Second, in the ‘Dumb’ scenario, only the original forecast errors in demand and wind power forecasts are corrected. The balancing includes only very little re-organization of the power plant schedules. In ‘Smart’ scenarios, it becomes economic to re-organize the original power plant schedules and hence there is much more balancing transfers in the ‘Smart’ scenario.

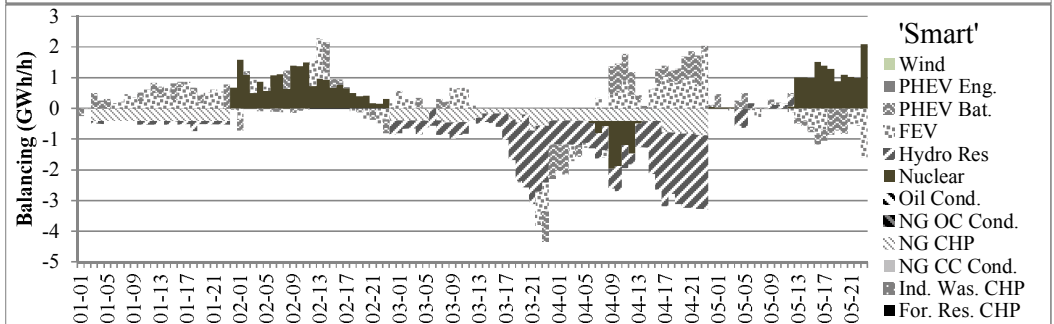
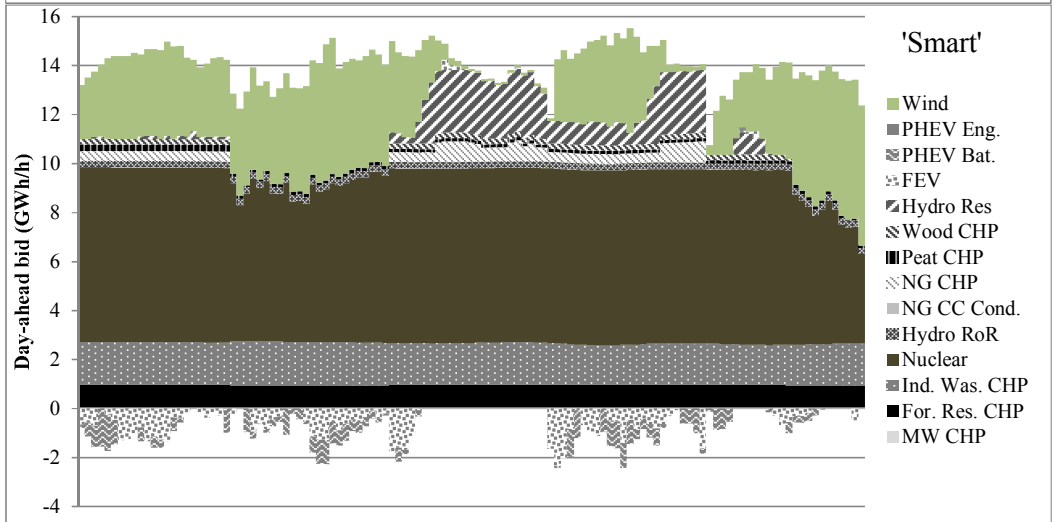
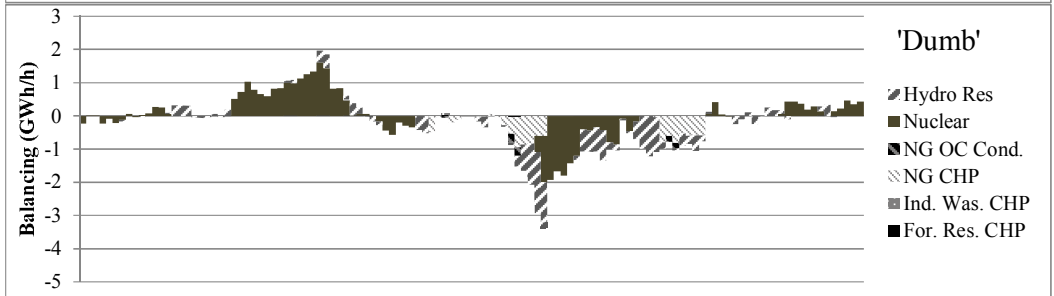
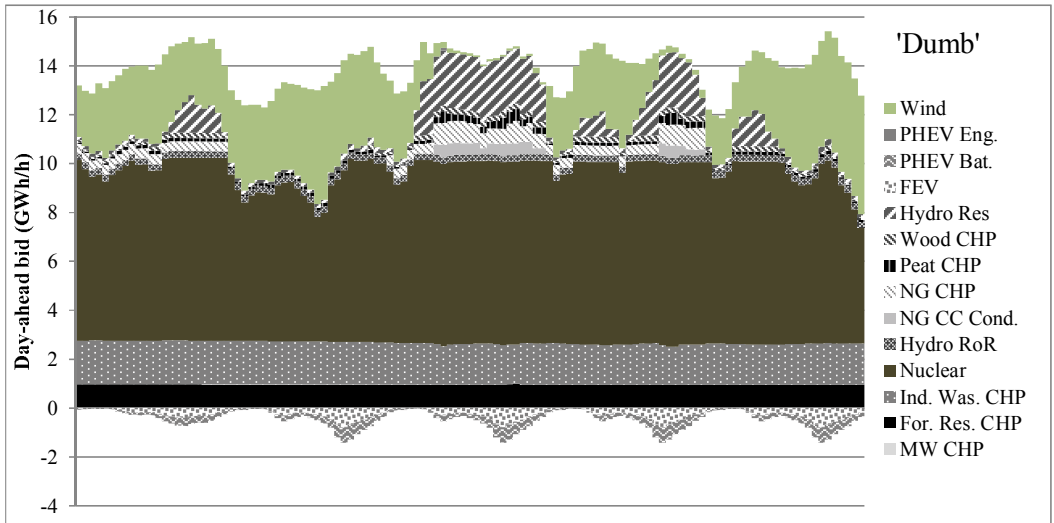
On the next page:

Figure 7. Day-ahead power plant schedules for four days in the ‘Dumb’ scenario.

Figure 8. Intraday balancing for four days in the ‘Dumb’ scenario.

Figure 9. Day-ahead power plant schedules for four days in the ‘Smart’ scenario.

Figure 10. Intraday balancing for four days in the ‘Smart’ scenario.



V. DISCUSSION

Some power plants receive a net loss in the WILMAR runs (Figure 6). Balmorel does not optimize investments based on market revenue – it minimizes total system costs and approaches long-term marginal cost equilibrium. This means that power plants that serve the high price hours are not able to recapture their fixed costs, since they set the market price based on their short-term marginal costs in WILMAR.

The accuracy of the results is limited, since the investment model does not see uncertainty of wind power forecasts. The omission of short-term uncertainty may be a problem for investment models in power systems with high amount of uncertain generation. If uncertainty was included already in the generation planning phase, higher share of wind power should have induced more flexibility in the generation fleet. More flexibility should have resulted in smaller balancing costs. Hence, the result that EVs decrease balancing costs considerably is uncertain. However, energy balancing with EVs should be less expensive than with thermal power plants. Changing the charging time creates only minimal costs when the enabling system has been built. In contrast, the use of e.g. open cycle gas turbines means that fuel is used in a low efficiency power plant, which increases the overall fuel use in the system.

The results have assumed that the charging time of EVs can be changed without a cost as long as it is feasible from the vehicle use perspective. However, there is a cost for setting up the system and a cost for operating the system. These need to be recuperated from the operational savings, or more correctly, from the power markets. At this point it is unclear how large the variable operating costs would be. Variable operating costs of EVs would affect wind power balancing costs directly, as these would be reflected in the real time prices. The fixed operating costs and investment costs would have an indirect effect, since if they are deemed too high, the investments will not be made and there will be less EVs that participate in the balancing of the power system.

For V2G, the results have assumed a round-trip efficiency of 85% and a variable cost of 10 €/MWh due to wear and tear. The latter should be a function of depth-of-discharge and it should be varied to show sensitivity, since there are many different battery chemistries and it is highly uncertain which ones will be predominant in future EVs. Other factors for sensitivity and scenario analysis would include different wind power penetrations, EV penetrations, power plant portfolios, and fuel prices. Before more of this done, it is too early to conclude how large is the impact of EVs for wind power balancing or for coping with the wind power variability. However, the mechanisms are visible in the modeling results so far and the direction of the impacts is clear. Wind power balancing costs are reduced with EVs.

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VII. BIOGRAPHIES



Juha Kiviluoma (M.Sc., Env.), Senior Scientist and Team Manager for Wind Integration. His main interest is economic integration of variable power generation. Juha uses and develops stochastic unit commitment models and generation planning models, including model and database development for reservoir hydro power, EVs and heat storages combined with electric heating.



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