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Quantifying the Long-term Power System Benefits of Electric Vehicles

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Abstract—The re-emergence of battery electric vehicles presents a potentially vast flexible resource to the power system at a time when renewable generation is pushing the ability of power systems to respond to increased levels of variability in production. Large installed quantities of wind and solar power in certain systems will cause changes in the operation of conventional generators that, over time, will reduce the economic feasibility of cost-effective but inflexible forms of generation. This can be avoided if electric vehicles can be used to mitigate the overall level of system variability by charging at times when production by conventional generators is at its lowest. This paper presents a methodology for determining the degree to which electric vehicles will influence future generation plant investment and a means of calculating the reduction in total system costs owing to the presence of optimally charged electric vehicles. This model is applied to a test system based on the state of Texas. It is found that the long-term benefits of electric vehicles are significant and continue to increase for all vehicle penetration levels studied. However, the relationship between levels of installed variable renewables and electric vehicle benefit was found to be highly dependent on the extent to which both of these parameters influenced the least-cost plant portfolio.

I. INTRODUCTION

ALL electric and hybrid electric powertrains are primed to become mainstream vehicle propulsion technologies in the coming years [1]. While this renewed interest in electric motive power may have arisen in response to high levels of vehicle emissions, the consequences of a potential electrification of transportation will extend far beyond this sector. The electric power industry, for its part, has already started to prepare. Vehicle charging standards have been created [2], charging points installed and large numbers of studies conducted on the projected impact on system operation [3], [4] and distribution grids [5], [6].

The transport sector accounts for roughly a quarter [7] of energy consumed in OECD. If even a portion of this energy, currently supplied in the form of liquid fuels, was displaced by electrical energy from the bulk power system, it would instigate very significant changes in the control, operation and planning of the electrical system. The quantity of generation

plant on a system is determined by peak demands on the system, which makes for substantial under-utilization of generation assets at other times. As electric vehicles would largely be parked and available for charging at night, when demand is low, they could be compelled or incentivized to charge at this time. This would increase utilization of generation plant, which over time, would justify investment in a greater portion of more costly, but higher efficiency plant, yielding an overall reduction in costs and harmful emissions. The benefits would extend beyond an improved demand profile. A major cost for power producers is in plant cycling, which refers to the starting and stopping of generating units, and large, rapid changes in their output, termed ramping. The costs of these operational modes are particularly high for large generating units [8], [9]. High levels of variability of production results not only in increased cycling costs for these units but also a general reduction in their utilization, so as to avoid these costs. This is being exacerbated by increasing quantities of variable renewable generation [10]. Electric vehicles could thus over time, reduce the variability costs associated with variable renewables and where preferable, facilitate even greater quantities of renewable generation. More generally, any form of flexible load can be used to reduce costs of preferable, but constrained forms of generation. In addition to variable renewables and units unsuited to cycling, this category includes temporally constrained units, such as large, slow-start generators, and technologies not designed for ramping behavior, such as nuclear fission plant.

This paper seeks to quantify the extent to which electric vehicles can positively influence the long-term evolution of the optimal installed generation plant. A capacity expansion model has been created for this purpose. Scheduling of generation in the model is achieved using a new mixed-integer unit commitment and dispatch algorithm. Previous work in this area has included more types of flexible loads [11] or has studied much larger systems [12], but are limited by using dispatch models for scheduling generators and are thus less suited to systems with high levels of variability.

II. METHODOLOGY

To quantify the long-term benefit of electric vehicles to the power system, a generation planning model is required. Here, this consists of two parts: a capacity expansion model for determining and selecting expansion options and a unit-commitment and dispatch model for calculating the operational costs of each expansion option, at each time-step.

In much of the world, electricity is bought and sold on energy markets and new generation is financed by profit-

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```

foreach study year do
  | update generation costs;
  | apply retirements;
  | determine expansion options;
  | foreach expansion option do
  | | schedule plant for plant life;
  | end
  | select least cost expansion;
end

```

Fig. 1. Overview of Capacity Expansion Methodology.

maximizing private investors. However, this analysis assumes that generator scheduling and investment is conducted on the basis of cost minimization. While not necessarily representative of the outcomes of certain market designs, cost-minimization corresponds to the outcome of an ideal market by determining the most economically efficient solution. It also lends to a simpler model from which conclusions can be drawn from with more ease.

A. Capacity Expansion Algorithm

In this model, in the first year, the least-cost combination of plant is determined by considering all combinations that would meet the minimum quantity of capacity. A technique could be used to reduce the number of portfolios to evaluate but the scheduling algorithm used is very computationally efficient and so there is little to be gained from using a reduction technique for this task. In addition, the problems associated with the discrete nature of generation plant and the non-linearity of portfolio optimization are avoided. Once the initial portfolio is determined, the expansion algorithm loops forward through the *study horizon*.

Each year, the quantity of additional capacity required is determined by means of a capacity margin. Annual time-series are defined for peak demand and generator retirements. Generator retirements are assigned in an even manner for each particular plant type. Generation expansions can then be determined for the whole of the study horizon, while the actual generation costs of the plant are determined over a longer horizon, termed the *plant-life horizon*. The generation costs of any plant built over the study horizon is determined for its whole plant life. The length of the plant-life horizon is thus the longest plant-life plus the length of the study horizon minus one.

The number of possible expansion solutions for any significant number of units operating over a reasonable number of years is very large. For simplicity, method that reduces the number of combinations is used. When the quantity of generation in a particular year falls below the capacity margin, all expansion combinations that would provide sufficient plant are determined. Least-cost schedules for each of these expansion options are then created for a period equal to the maximum plant-life of the plant-types. Finally, the lowest cost option is then selected. The process is summarized in Fig. 1.

B. Scheduling Algorithm

Unit-commitment and dispatch optimization programs solved using generic mixed-integer solvers tend to take significant lengths of time to reach solutions that satisfy the specified optimality gap, i.e. are sufficiently close to the dual solution. Optimization programs have the advantage of flexibility and ease-of-specification, but in the absence of solvers designed for solving unit-commitment and dispatch, or without passing of effective problem specific information to the solver, a great many un-necessary decision variable combinations are evaluated in the search for the solution.

Here, an algorithm has been written to determine generator schedules in a comprehensive and efficient manner. A simplification to facilitate this, is to split generator types between units whose start costs and minimum outputs are sufficiently low, such that treating their costs as linear variables from zero is a reasonable assumption. These units, termed *flexible units* here, include open-cycle generators and can be aggregated into blocks of generation by type of generator without any change in the result. The remainder, the *inflexible units*, are treated as discrete units, with specific output ranges, no-load costs, incremental costs and start costs.

Spinning reserve is treated as an input, with reserve-demand based on the largest installed unit. This could be extended by adding an amount for the level of wind being produced. Additionally, electric vehicles and other technologies that can contribute to reserve targets could be included.

The algorithm first determines the unit commitment. Each time-step the capacity of online inflexible generation is compared to the demand, net of wind generation and reserve demand. If it is less, then a process to determine whether a start would be optimal, called the *rise* begins. This involves calculating the reduction in costs from utilizing an extra unit of any of the installed types, against using the available flexible generation. As the rise iterates forward in time, if the cost saving for any of the inflexible types exceeds the cost of the starting that type, a unit of that type will start. The rise will terminate if all of the cumulative savings for all the inflexible types become negative. After a rise is terminated, execution resumes at the latter of the time-step after the last time-step at which a start occurred, or the last time-step where the net-demand was such that the online inflexible units would have become part-loaded. This would be the first time-step at which a unit stop might be worthwhile.

Unit stops are evaluated, by a procedure termed the *fall*: When the net-demand reduces such that the online inflexible generation would be part-loaded, the cumulative cost of maintaining this quantity of generation online is evaluated. When this cumulative cost exceeds the cost of restarting the unit, a unit stop for that unit type will be scheduled and the process will repeat from the time-step at which it previously start. The procedure will exit if the minimum number of online units is reached, given the capacity of alternatives and the defined minimum number of online inflexible units.

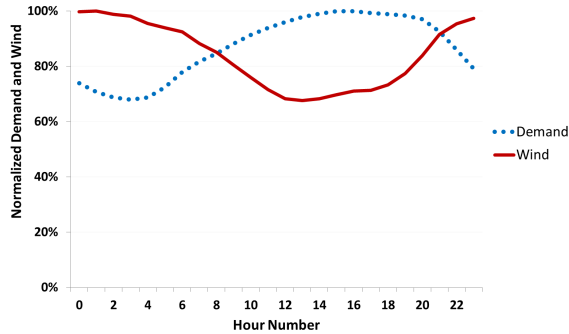


Fig. 2. ERCOT (2009) - normalized hourly averages of system demand and wind production.

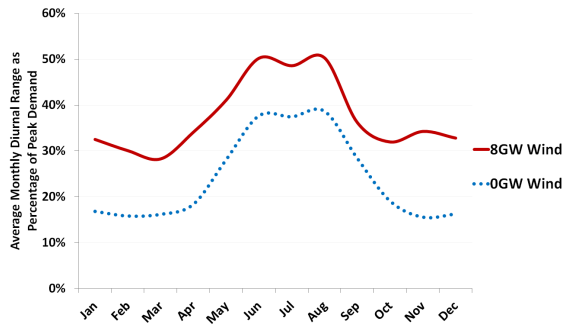


Fig. 3. ERCOT (2009) - Daily max. minus daily min. net-demand, averaged by month, as a percentage of annual peak demand for 0 and 8GW of installed wind.

C. Electric Vehicle Scheduling

Electric vehicles are scheduled in advance of the main scheduling algorithm. Their demand is allocated daily, in a manner that maximizes the level of demand, net of wind generation. The rate of system charging is constrained by the level of system availability. The quantity of aggregate daily electric vehicle demand and charging availability is discussed in Section III.

III. TEST SYSTEM & INPUT DATA

The test system used is based on the Electric Reliability Council of Texas (ERCOT). Historical hourly system demand and wind time-series from 2009 have been used [13]. The demand series was scaled to 10GW peak demand. The system exhibits a relatively large degree of diurnal, i.e. within day, variability, where the average demand minimum is less than 70% of the daily peak (Fig. 2). What's most interesting about the diurnal characteristics of the ERCOT data is the strong negative correlation between wind and demand. This indicates that for increasing wind, the level of system variability should increase markedly. The extend of this is indicated in Fig. 3 where for a high installed capacity of wind, the average level of diurnal variability increases substantially and in a seasonal manner.

A limited quantity of state-level transport data was available. As an approximation, the daily transport energy use was derived from data for the annual gasoline consumption for the state of Texas [14]. This figured was first converted from

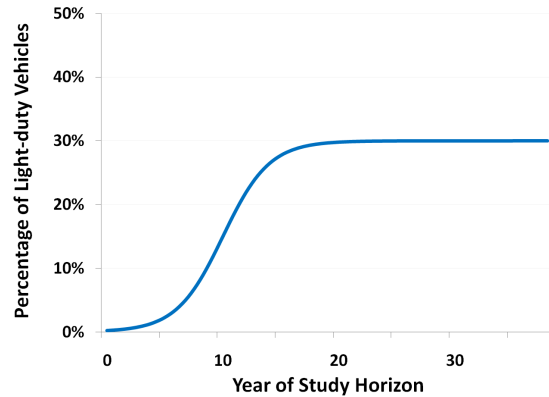


Fig. 4. Assumed electric vehicle penetration over the study horizon

barrels of gasoline a year to MWh of energy per day. An assumed efficiency factor was then created by taking the average fuel economy of light-duty vehicles in the state [15] and dividing it by the energy consumption of a comparable electric vehicle [16]. For the set of results discussed in section IV-A, it was assumed that over the study horizon the penetration of electric vehicles would grow in logistic manner from year zero and saturating by approximately year 20 at 30% of light-duty vehicles (Fig. 4). At this penetration level, the average daily energy demand for the system was $10.4GWh$.

It was assumed that all electric vehicle charging took place in the homes of the owners and once connected the vehicles could charge at up to $4kW$. This is perhaps a reasonable figure given that vehicles will tend to charge during periods of low household demand when the typical 120V supply voltage on a 100A household circuit would have ample capacity for extra load. Further, the average charge rate over the period that vehicles are connected is a great deal below this limit.

Vehicles were only considered as flexible loads in this study, though there is a clear opportunity for vehicles to provide certain categories of positive reserve as well as, in the long-term, mitigating the need for very-low utilization peaking plant. The system availability of connected vehicles was determined by way of time of departure data from the US census [17]. It was assumed that on average, vehicles returned 9 hours after their departure, roughly corresponding to twice the average commute time plus an 8 hour working day. This resulting availability series is given in Fig. 5.

The expected life of the generation plant is quite high, which made the process of selecting a fuel price trajectory for the study horizon challenging. The level of fuel price variation long into the past may not adequately reflect the level of contemporary and future fuel price variation as the scarcity of these resources increases into the future. Instead, a series of monthly average coal and natural gas prices paid by generators in Texas was chosen. While month-to-month variations may not reflect year-to-year changes, here the costs over the life of the plant is sought, so the probability of prices of a fuel occurring takes precedence over the auto-correlation of the prices of that fuel. A $\$20 CO_2$ tax was applied to the fuel prices, consistent with recent prices in the European Emissions

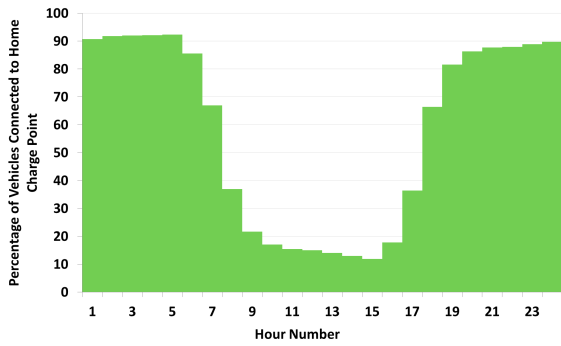


Fig. 5. Electric vehicle hourly availability as percentage of total electric vehicles.

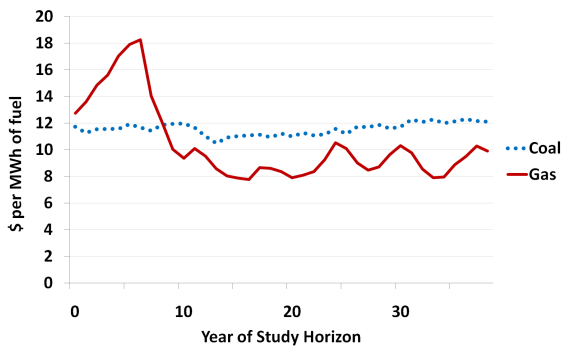


Fig. 6. Prices of coal and natural gas over the study horizon

Technology Type	Min. Output MW	Max. Output MW	Thermal Efficiency %
Inflexible	Coal	200	34
	CCGT	200	56
Flexible	OCGT		35

TABLE I
GENERATING UNIT PARAMETERS

Technology Type	Start Cost \$	Annual Fixed Costs \$/MW	Plant Lifetime years
Inflexible	Coal	50,000	30
	CCGT	100,000	20
Flexible	OCGT	34,821	20

TABLE II
GENERATING UNIT PARAMETERS (CONTINUED)

Trading Scheme [18], the largest market for CO_2 emissions permits. The effect of the CO_2 tax is that it makes wind more competitive with the conventional technologies and also results in the lowest cost fuel changing over the course of the horizon (Fig. 6).

The plant types parameters are presented in Table I and II [8], [9], [19], [20]. The pertinent features are the large output range of the coal generation and the high efficiency and lower installed cost of the Combined Cycle Gas Turbine (CCGT) plant.

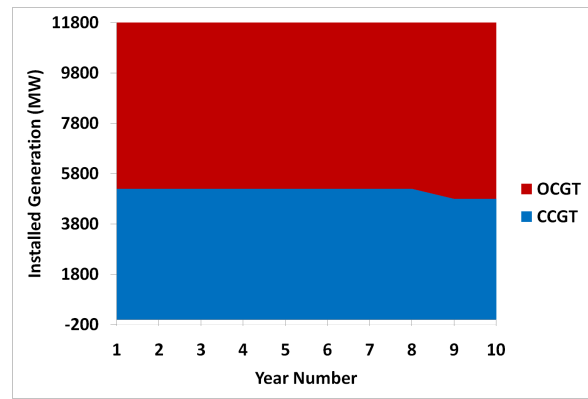


Fig. 7. Changes in plant mix for zero electric vehicles.

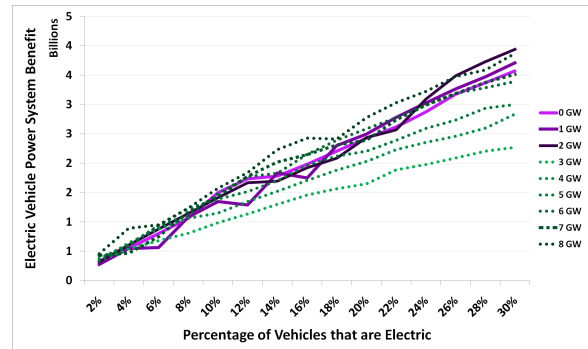


Fig. 8. Power system benefit (reduction in total costs) owing to electric vehicles.

IV. RESULTS

A. Evolution of Generation Mix

Taking the growth of electric vehicles as having the logistic form described in Fig. 4, it was sought to determine the resulting evolution of the generation plant mix. It was expected that the gradual proliferation of electric vehicles would result in a lag in the evolution of the generation mix. This was partly the case. In fact, changes in the portfolio mix for zero electric vehicles did not occur until year 9 (Fig. 7) but for the case with 30% of vehicles as electric, there was no change at all in the generation mix. This can be ascribed several causes. Foremost, the natural change in the generation mix for this case is an increase in flexible generation, as evidenced from the results of the zero electric vehicles case (Fig. 7). No reduction in the quantity of the more-efficient inflexible generation is thus an improvement. Secondly, the size of the generating units relative to the size of the test system means that moderate changes can be masked. Finally, the effect of the introduction of electric vehicles is averaged over 30 years, the early years of which there is a much smaller quantity of them.

B. Long-term Benefits

Electric vehicles charged in a manner that is optimal for the power system, act as a means of mitigating the costs associated with variability, which arise from the combination of the variability arising from renewable generation and the pre-existing demand variability. The results here are for a system

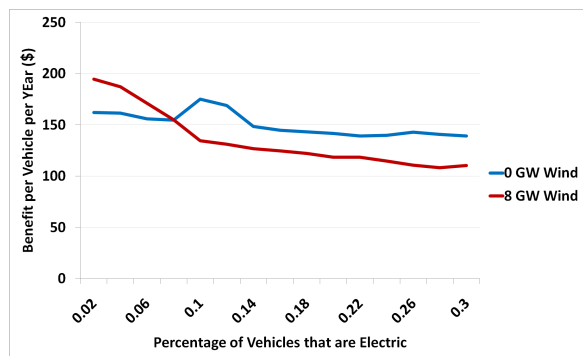


Fig. 9. Power system benefit attributable to electric vehicles, per vehicle-year.

with moderate demand variability, that increases rapidly with increasing installed wind. It should therefore be expected that for increasing wind, the power system benefits conferred by electric vehicles should increase, and perhaps at an increasing rate. However, it is seen (Fig. 8) that this hypothesis can break down in certain cases. In this set of results, the model was applied for levels of electric vehicles that were constant over the whole period, instead of the logistic growth model. It is seen that between 0 and 2GW of installed wind (solid line plots), the benefits are generally seen to increase, but at 3GW of installed wind, there is a stark drop in the benefits derived from electric vehicles, which only gradually recovers as the level of installed wind increases further (dotted line plots). The reason why this occurs is that at a certain level of wind the least cost initial portfolio changes from having a large installed capacity of coal and CCGT plant, to one that contains a much reduced combined quantity of these plant types. As more wind is introduced, the utilization of plant falls, which reduces the economic feasibility of high capital cost plant such as coal generation. The consequence is that for reduced level of coal and CCGT plant, a greater portion of the power production when charging is occurring is being generated by the more costly open-cycle plant.

The benefits appear to be nearly linear in all cases. It was expected that the benefits would saturate for increasing electric vehicles since, given the natural shape of demand valleys, increases in daily charging energy should yield successively smaller increases in the minimum demand. This indeed appears to be the case, but is more evident when the benefits are viewed on a per-vehicle basis (Fig. 9). For the zero wind case, the benefit per vehicle decreases for increasing numbers of vehicles, while for the highest wind case, the benefits are initially higher but decrease at a higher rate, especially at low levels of electric vehicles.

V. CONCLUSIONS

For the system considered, it was shown that electric vehicles that are charged in a manner beneficial to power system operations can provide a substantial reduction in system costs and as a result, can positively influence future cost-optimal expansion of power generation. The level of this reduction in costs is specific to the extent of demand variability and the level of variable renewables. Systems with high levels

of demand variability or plans for large amounts of variable renewables should gain the most. However, in the test system used, it was found that the relationship between levels of installed wind and electric vehicle power system benefit is not straight-forward. Even though vehicle charging mitigates the variability impacts of wind power, wind power will also strongly influence the composition of the generation portfolio in ways that may reduce the electric vehicle benefit. This underlines the importance of considering changes in generation investments when analyzing the impact of electric vehicles.

VI. FURTHER WORK

Annual benefit per vehicle, as presented in Fig. 9, could also be a measure used in the calculation of an appropriate subsidy for electric vehicles. This could be combined with the integration cost of electric vehicles and any other power system costs or benefits. If this amount was found to be positive and significant in size, a financial mechanism could be designed to compensate electric vehicle owners by some portion of that amount. This would be mutually beneficial whilst acting as a stimulus for the adoption of electric vehicles.

There are many technologies that can provide flexible power and energy demand and supply in the smart-grid context. The use of flexible heating and cooling has been considered and could be integrated into the methodology presented here. However there are many other sources of flexibility in areas where the use of energy has always been flexible in a temporal sense, but where there was insufficient value to be gained from monetizing that flexibility. This technologies could provide a very large amount of flexibility in aggregate. It would be useful to determine the specific technologies where most is to be gained when put in competition, given their various constraining features and costs.

The analysis here and the conclusions drawn are based on cost-minimization. The market outcome could be substantially different and the study of this could yield insights in how market designs could be improved to best account for technologies that provide flexibility to the power system.

There are several potential functions of electric vehicles that were not considered. Aside from their use in various reserve categories, and as a replacement for peaking generation, they could be effective in providing power during start-up of temporally constrained units. Temporal constraints could be included in the scheduling algorithm to facilitate this.

Finally, CO_2 emissions per distance traveled are estimated for conventional vehicles for use in tax and subsidy calculations and also as a performance characteristic. An analogous figure can be determined for electric vehicles by calculating the power generation emissions for the periods that vehicles are being charged. By considering the long-term impact of the electric vehicles on the generation mix, as has been conducted here, a better estimation of this metric can be determined.

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