Renewable Energy Supply for Electric Vehicle Operations in California

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Abstract

Due to technological progress, policy thrust and economic circumstances, the large scale integration of renewable energy sources such as wind and solar power is becoming a reality in California, however the variable and unpredictable supply of these renewable resources poses a significant obstacle to their integration. At the same time we are witnessing a strong thrust towards the large scale deployment of electric vehicles which can ideally complement renewable power supply by acting as storage buffers for maintaining stability in the presence of large amounts of renewable power. In this paper we use California system data for identifying the degree to which wind and solar power supply correlate with battery electric vehicle loads. Moreover, in order to assess the economic viability of utilizing renewable resources for powering electric vehicles we adopt the point of view of a profit maximizing electric vehicle service provider which seeks an optimal portfolio of energy supply contracts for satisfying electric vehicle energy demand, and we find that wind generation is a cost competitive option, whereas solar power supply does not appear to be an economically viable option. We also demonstrate how smart charging strategies for satisfying electric vehicle energy demand can lead to significant cost savings for the electric vehicle service provider.

1. Introduction

After 30 years of rapid technological development and owing to current economic, political and environmental circumstances, renewable energy sources such as wind and solar power are poised to become a mainstream energy source capable of supplying bulk

quantities of power to power systems. California, in particular, is providing fertile ground for renewable energy development. California already hosts 2493 MW of wind power, the second greatest installed capacity in the US, and in 2006 11% of the state energy consumption was supplied by wind energy [5]. Renewable power growth in California will continue as renewable energy is enjoying strong political support. Assembly Bill 32 has set a goal of cutting back greenhouse gas emissions to 1990 levels by 2020 and the Renewable Portfolio Standard (RPS) mandates 20% integration of renewable energy in California by 2010. In addition, the electricity market facilitates the trading of renewable power. The Market Redesign and Technology Upgrade (MRTU) which was launched in 2007 is a reform of the California electric power market which enables loads to bid into the market in order to mitigate the effects of renewable power variability. Independently from MRTU, the Participating Intermittent Resources Program (PIRP) which was launched in 2002 offers favorable treatment to wind generators by exempting them from various market penalties relating to supply deviations [5].

As wind and solar power are becoming a mainstream energy source, their random and variable fluctuation is becoming a serious impediment to their large scale integration. The unpredictable and variable supply of renewable power may result in balancing actions that range from ramping other generators, load following, primary and secondary control actions, to the upset of hour-ahead and day-ahead schedules. These balancing actions are costly, lead to air pollution, cause wear and tear to machinery and require significant investments in system backup. Empirical and academic studies have placed an estimate on the costs resulting from wind variability at a range of 0 to 7 $/MWh [7], [13], [14]. In addition, renewable power is often adversely correlated with system supply and demand patterns, and may be discarded even when it is abundantly available [5].

The large scale deployment of electric vehicles in transportation networks offers system operators access to an extraordinary storage resource which can strongly mitigate the aforementioned operational disturbances. EVs represent an extremely flexible class of electric loads and it is natural to consider the potential of charging vehicles according to the supply of non-dispatchable renewable energy sources in order to increase our reliance on renewable energy generation without compromising grid stability.

Apart from offering benefits to grid operators in terms of load response, the utilization of EV batteries as storage buffers for renewable energy results in a direct substitution of petroleum by renewable power for fueling the transportation sector. In 2007 the U.S. transportation sector accounted for 29% of national annual energy consumption, and it was almost exclusively fueled by oil [1]. It is therefore evident that EVs present a unique opportunity for accelerating our transition towards cleaner energy sources.

From an academic standpoint, the challenge of actively utilizing electric vehicles and other flexible resources for the purpose of mitigating renewable power variability offers fertile ground for the application of various optimization techniques. The utilization of load resources can be considered as a generalization of the traditional unit commitment problem [12] where, in addition to the optimal commitment and operation of generation

resources, we are also able to actively dispatch certain classes of flexible load resources. Due to the potentially large number of flexible load resources the use of unit commitment models and their associated solution techniques may be hindered by computational limitations, therefore an alternative approach could be efficient heuristic scheduling algorithms for determining the priority service of flexible loads [2], or the use of suboptimal dynamic programming techniques [3].

In the following sections we use an annual dataset of California solar and wind power supply to analyze the potential of using renewable power for charging EVs. We first estimate the extent to which renewable energy capacity can satisfy EV energy demand solely based on the relative pattern of renewable supply and EV demand. Next we assess the economic competitiveness of renewable energy with nonrenewable energy sources by solving for the optimal portfolio of supply contracts which can cover EV energy demand. We also assess the sensitivity of our results to various assumed model parameters. Finally, we explore the potential economic savings from "smart charging," i.e. sophisticated charging strategies which shift charging off of peak hours and accommodate increased utilization of renewable power.

In Section 2 we describe the central assumptions and methodology of our analysis. In Section 3 we present our key results, in Section 4 we discuss future research directions and in section 5 we summarize our conclusions.

2. Methodology

In our analysis we consider the task of a service provider which has the objective of supplying electricity to EVs in a cost effective and reliable fashion. In particular, the service provider decides when EV batteries are charged, and strives to postpone charging during hours of low system demand while ensuring that charging is not postponed long enough that vehicles run out of energy en-route. This provider could either be the local utility or an independent load management entity. Due to regulatory constraints we assume that the EV service provider is required to offset the emissions of EV energy supply, either by directly supplying solar or wind power, or by purchasing the appropriate quantity of renewable energy credits (RECs) to neutralize nonrenewable energy supply to EVs. Moreover, we assume that the EV service provider can select from a mix of wind, solar, and fossil fuel contracts with the objective of minimizing its operational costs.[1] From the point of view of the service provider, wind and solar power supply offer the advantage of contributing to the commitment for satisfying demand with renewable energy sources. On the other hand, these resources are unreliable, and if faced with a shortage we assume that the service provider must procure energy from the electricity spot market. Fossil fuel generators, in contrast, are more reliable and lower cost; however, their emissions must be offset by the purchase of RECs.

[1] For the vehicle adoption level which we consider in our simulation scenarios (100,000 cars), the required renewable supply capacity does not exceed the installed capacity of the California system [5].

2.1 Model formulation

The service provider solves a two-stage optimization problem. In the first stage the service provider needs to decide the capacity of contracted fossil fuel generation $q_{ff'}$ wind power generation q_w and solar power generation q_s. As mentioned previously, the purchased amount of fossil fuel generation is supplied throughout the year reliably, whereas the corresponding wind and solar power capacity result in randomly varying power generation described by the processes w_t, s_t. Given these higher-level decisions the service provider then solves the following dynamic optimization problem for charging electric vehicles:

$$P(q_w, q_s, q_{ff}):$$

$$\min_{\pi} E\left\{\sum_{t=1}^{8760} \lambda_t \sum_{i \in I} c_{t,i} + \lambda_{\text{rec}} e_{\text{rec}}\right\}$$

s.t

$$0 \le c_{t,i} \le C$$

$$\sum_{i \in I} c_{t,i} \le w_t + s_t + q_{ff}$$

$$\sum_{t=T_i^a}^{T_i^d} c_{t,i} = r_i$$

$$c_{t,i} = 0, t \le T_i^a$$

$$\sum_{t=1}^{8760} (w_t + s_t) + e_{\text{rec}} = \sum_{i \in I} r_i$$

where $c_{t,i}$ is the amount of power supplied to user i in period t, λ_t is the hour-ahead market price of electricity which is a random process, e_{rec} is the amount of RECs purchased by the service provider and λ_{rec} is the purchasing price, C is the maximum rate at which vehicles absorb power, r_i is the amount of energy required to charge the vehicle of user i, and T_i^a and T_i^d are the arrival and departure times of user i respectively. I is the set of users that the service provider is serving. π is a policy function which maps the current state of the system to an action vector $c_{t,i}, i \in I$, for the current period t.

The first constraint requires that the power supplied to vehicles be nonnegative and not exceed the power rating of the vehicles. The second constraint implies that the amount of power allocated to vehicles in period t does not exceed the total amount of power available to the service provider. The third constraint requires that the energy demand of vehicles be fully satisfied within their designated deadlines and the fourth constraint prohibits supplying power to vehicles before their arrival time. The final constraint imposes that the service provider either fully cover customer demand via renewable sources, or that the emissions be fully offset by REC purchases.

The problem presented above is a sequential optimization problem under uncertainty and dynamic programming can be used for solving this problem. In fact, it is the second constraint which complicates the problem since in the absence of this constraint the problem would decompose to the individual users and would reduce to solving a number of deterministic optimal control problems equal to the number of users. Although dynamic programming can be used for solving this problem in principal, the curse of dimensionality renders dynamic programming as a computationally prohibitive approach. In this paper we are using a suboptimal policy which allocates during each period the greatest possible amount of contracted resources to standby vehicles:

- If all standby vehicles can be satisfied by the contracted resources, then the all vehicles receive power and the remaining supply is discarded.
- If standby vehicle demand exceeds the amount of contracted supply for the current period and vehicle charging can be postponed without violation of charging deadlines, then as many vehicles as possible are charged with existing resources and the charging of remaining vehicles is deferred.
- If current period supply does not suffice for charging all vehicles and postponing charging is not possible without violating the charging deadlines, then all vehicles are charged in the current period with contracted supply resources and the deficit of supply is purchased from the hour-ahead market.

The aforementioned charging policy is not suboptimal. There has been an extensive line of research on sophisticated heuristic policies for dynamic programming which could inspire alternative approaches for this specific application, including certainty equivalent control [3] and approximate dynamic programming [9], [10]. Finally, another fruitful technique of attacking the problem above would be to derive properties about the optimal policy and the value function from the Bellman equations [11]. For example, it is possible to show that a simpler version of the aforementioned problem has a bang-bang form which simplifies the computation of an optimal solution by limiting the search of the action space.

Once a heuristic charging policy has been determined it is possible to solve the higher level problem of determining an optimal choice of $q_{ff'}$ q_w and q_s by solving the following problem:

$$\min_{q_{ff}, q_w, q_s} \quad P^{\pi}(q_{ff}, q_w, q_s) + \lambda_{ff} q_{ff} + \lambda_w q_w + \lambda_s q_s$$

where $P^{\pi}(q_{ff}, q_w, q_s)$ is the expected cost of the lower level problem by adopting policy π, and potentially, λ_w, and λ_s are the prices of the fossil fuel, wind power and solar power contracts respectively. In our case this problem was solved by brute force by searching over a discrete set of contracted quantities and choosing the portfolio with the lowest expected cost.

2.2 Model data

We assumed that vehicle batteries have charging capacity of 20 kWh, power rating 3 kW and a mileage of 0.25 kWh per mile, which implies that cars can travel a distance of 80 miles without recharging. We imposed two deadlines for charging vehicles during a 24-hour time period: the morning deadline is at 6 a.m. and the evening deadline is at 4 p.m. This would be a reasonable charging strategy which would ensure that all drivers have adequate energy stored in their vehocles to ensure that they can commute to work and back home without emptying their batteries en-route. All drivers are assumed to have a 25-mile commute to work and back home. This long commute is due to the fact that an EV service provider may prefer to target long-range drivers first, since they have the greatest financial incentive to switch to EVs. The arrival times of drivers to their destinations are assumed to be known in advance to the service provider. In figure 1 the intensity of arrival times is shown to vary throughout the day, with most arrivals concentrating around 9 a.m. when drivers arrive to work and 6-8 p.m. when drivers arrive back home.

The wind power supply data used for the simulations are based on a wind speed model developed by the National Renewable Energy Laboratory [6]. We used hourly data for six locations in California for the full duration of 2004. As prescribed in [6], we used the power curve characteristics of Vestas V90 3 MW generators with a cut-in speed of 4 m/s, a cut-off speed of 25 m/s, and a speed of 15 m/s for maximal output. Generators located in the same site were assumed to have identical outputs. In order to model solar generation, we used hourly insolation data for the full duration of 2005 from the solar database of the National Solar Radiation Database (http://www.nrel.gov/rredc/). We assumed that the solar panels have 20% efficiency.

In order to model the hour-ahead market prices in California, we used the average hourly ex post energy prices for the full duration of 2006, retrieved from the California Independent System Operator database (http://oasis.caiso.com). In addition, for the baseline scenario we assumed a price of $45/MWh for fossil fueled generation constracts

[7], a price of $60/MWh for wind power generation contracts [7], a price of $170/MWh for solar power generation contracts [8], and a price of $20/MWh for RECs.

3. Results

3.1 Renewable energy supply relative to EV energy demand

The graphs in figure 1 are based on annual data which has been averaged over each hour of the day. We have superimposed wind and solar power supply on EV demand and we have normalized the graphs with respect to their maximal value in order to highlight their relative patterns. Note that EV energy consumption refers to the energy consumed by the vehicles, not the energy which is supplied to the vehicles by the service provider. Although EVs consume energy according to the blue curve, the time at which they are charged can be adjusted in order to better correlate with solar and wind power supply. Therefore, although renewable supply peaks when EV consumption is low, morning charges can be postponed to coincide with solar power supply and evening charges can be similarly postponed to coincide with wind power supply. It should be noted that the actual day-to-day and intra-hour variation of the supply sources differs strongly from the average behavior shown in figures 1-3.

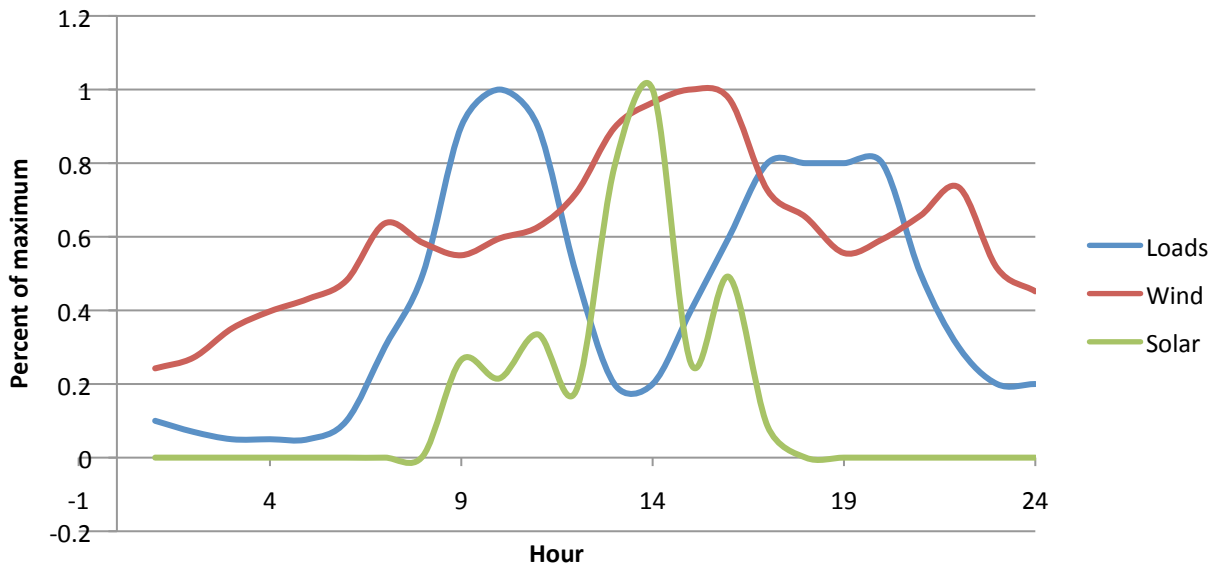


Figure 1: Annual average of daily solar power supply, wind power supply and EV energy consumption.

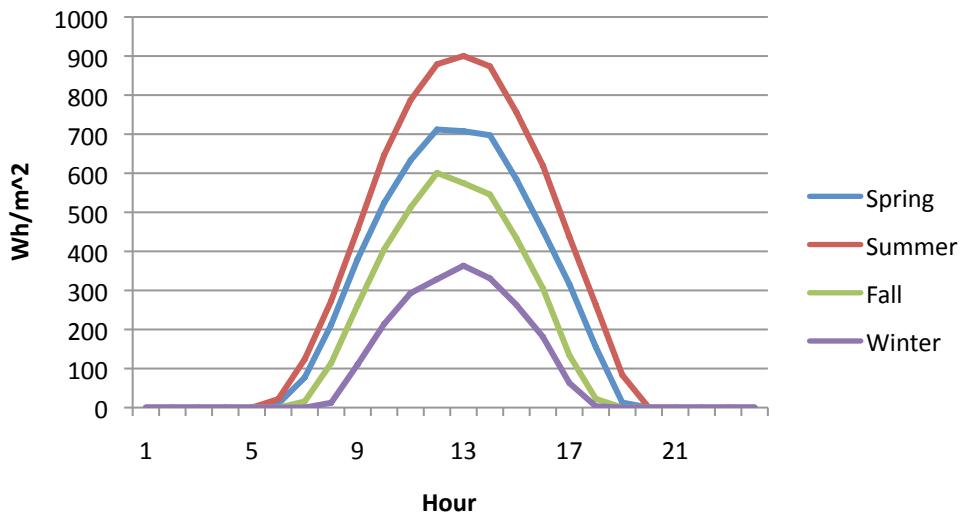


Figure 2: Average daily solar power intensity by season.

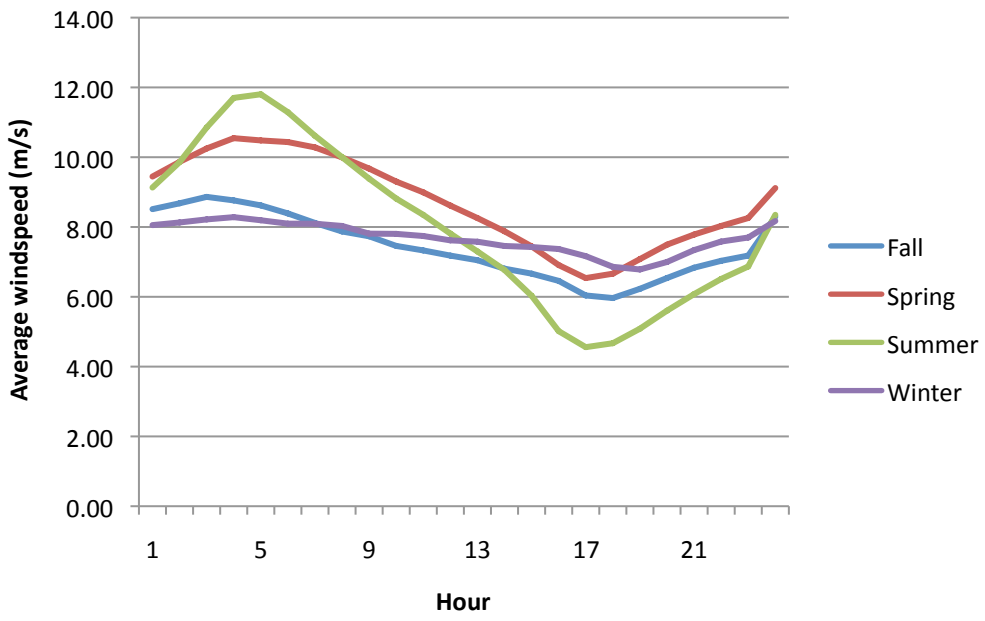


Figure 3: Average daily wind speed by season.

The graphs in figures 2 and 3 are based on the same data as figure 1, but have been broken down by season in order to highlight the impacts of seasonality on renewable energy availability. We observe that both wind speed and solar intensity follow the same average pattern throughout the day for all seasons, however the variability varies significantly between seasons. Wind power is most variable during the summer, whereas it is most regular during the winter. Likewise, solar intensity varies most during the summer, and its summer peak is three times greater than its winter peak. Figure 3 also confirms that wind power supply is greatest during the night in California. This further

validates the value of EVs for renewable energy integration, since it is during the night that wind is least needed by the system operator and is often discarded.

Table 1 shows the simulation results of dedicating various combinations of wind and solar power capacity to 100,000 vehicles where we have used the charging algorithm described in section 2.1. The table shows the fraction of EV energy demand which can be covered by renewable energy by employing the simple charging strategy described in section 2.1. We can make certain observations from table 1. Comparing the first row and column, we observe that each unit of wind power capacity can serve a greater fraction of EVs than an equivalent unit of solar power capacity. Diagonal cell (i,i) yields better results than the first-row cell $(1,2i)$ but worse results than the first-column cell $(2i,1)$ indicating that a given unit of wind power capacity is more effective than a balanced mixture of wind and solar power capacity which is more effective than a unit of solar power capacity. Moreover, by observing the lower right area of the matrix we observe a saturation effect where significant increments in renewable power capacity yield minor improvements in load service.

Solar (MW)	0	30	60	90	120	150	180
Wind (MW)							
0	0.0	12.5	25.0	35.8	43.7	47.4	50.0
30	17.4	29.9	42.2	51.2	56.4	59.9	62.0
60	34.6	46.9	57.6	64.5	68.4	71.0	72.7
90	48.9	59.8	68.4	73.6	76.8	78.8	80.2
120	59.0	68.2	75.1	79.3	81.8	83.5	84.7
150	65.9	73.7	79.6	83.2	85.3	86.7	87.7
180	70.9	77.7	82.8	86.0	87.7	89.0	89.8

Table 1: Percentage (%) of EV energy demand satisfied by renewable energy sources (100,000 cars).

In table 2 we observe the tradeoff between load service and wind power utilization. As increasing capacity is dedicated to EV charging, an increasing fraction of the EV fleet can be served by wind power, however a relatively greater proportion of wind power supply is discarded due to its uncontrollable availability in unfavorable hours. Nevertheless, it is worth noting that we are able to serve 59% or more of the EV load while discarding less than 10.2% of the available wind power.

	Demand coverage (%)	Wind power utilization (%)
Wind (MW)		
30	17.4	100.0
60	34.6	99.8

90	48.9	96.6
120	59.0	89.8
150	65.9	81.6
180	70.9	74.0

Table 2: EV demand coverage and wind power utilization for various levels of wind power capacity (100,000 cars).

3.2 Baseline scenario

In this section we focus on identifying the optimal supply mix for providing electricity to 100,000 EVs at minimum cost. We compare this baseline scenario to alternative scenarios in the following sections. As we described in the methodology section, we assume the following prices for the baseline scenario: $45/MWh for fossil fuel contracts, $60/MWh for wind power generation contracts, $170/MWh for solar power generation contracts, and $20/MWh for RECs. According to our model, whenever excess renewable power is available to the EV service provider we assume that it is discarded. This assumption is justified by the fact that system operators cannot easily accommodate supply which becomes available upon short notice, therefore the owner of the supply contracts will be unable to supply the excess renewable power to the market if EVs cannot absorb it. This assumption can be relaxed in our model, but the results presented here assume that all excess energy is discarded.

By running our simulation model with various amounts of renewable and nonrenewable resources in the supply mix, we determined that the best option for the baseline case is a contract of 60 MW for wind power generation. No solar or dispatchable fossil fuel generation is included in the optimal supply mix. The proposed supply portfolio amounts to an annual cost of $30.5 million. This cost is broken down as follows: $8.6 million is expended in the wind energy supply contract, $15.6 million is expended in the hour-ahead market, and $6.3 million is expended in RECs. It is worth noting that the optimal solution suggests a conservative approach whereby the EV service provider covers only 32% of its needs with contracted wind power and prefers to purchase its remaining obligation in the form of REC credits. In fact, 99.8% of the wind supply is actually utilized by EVs, since the limited availability of contracted wind power rarely exceeds instantaneous EV energy demand.

In figure 4 we highlight the impact of seasonal variability in the baseline scenario. We observe considerable seasonal variation with maximum renewable energy supply to EVs occurring during the spring and minimum supply occurring during the fall. There is an 8% differential between the two seasons, which is a considerable fraction of the maximal supply which occurs during the spring (36%).

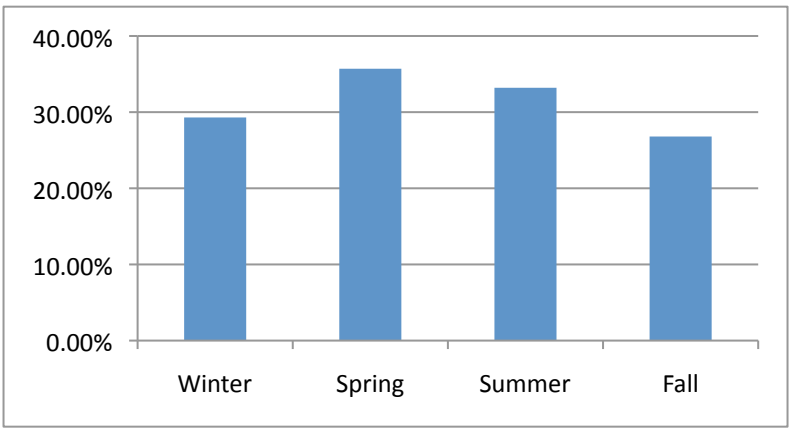


Figure 4: Percent of load satisfied by renewable energy sources by season for baseline scenario.

3.3 "Smart" charging

We have mentioned that in the baseline scenario all vehicles are fully charged at 6 a.m. and 4 p.m. This is a stringent constraint since the one-way commute of most drivers does not exceed the full capacity of the EV battery. If the EV service provider is able to adapt charging schedules to individual driving, it should be possible to relax the aforementioned policy by allocating each driver enough energy to ensure that the EV does not encounter an energy shortage en-route albeit without charging batteries at full capacity during the two deadlines. This would result in increased flexibility for the EV service provider, greater utilization of renewable power supply and reduced exposure to the hour-ahead market. The result of applying the relaxed constraint is shown in Figure 5, where we present hour-ahead market purchases and REC charges for three different charging strategies. The first is a naïve approach whereby customers are charged immediately as they connect their vehicles to the grid. The second is the baseline 6 a.m. – 4 p.m. charging strategy, and the third is a relaxed charging strategy whereby cars are charged at 75% of their full capacity at 6 a.m. and 4 p.m. As opposed to the first and second case, which result in an optimal portfolio which includes 60 MW of wind power, the third charging strategy results in an optimal portfolio which includes an additional 20 MW of wind power. We observe that refined charging strategies lead to cost savings of $5 million for the second case and $8 million for the third case, as compared to cost of the naïve strategy. It should also be noted that the third strategy does not result in supplying less energy to EVs, but instead results in supplying this energy at hours which are more favorable for the service provider.

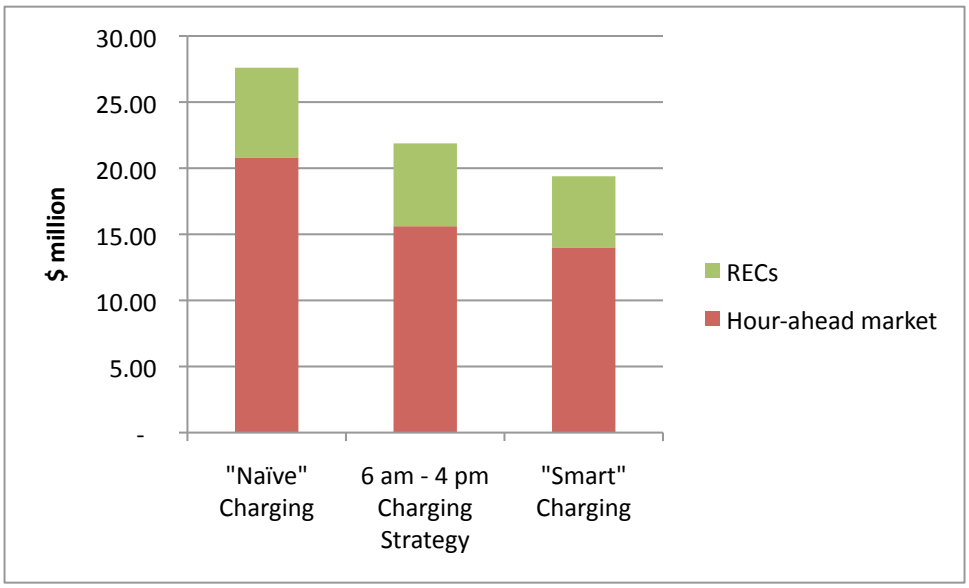
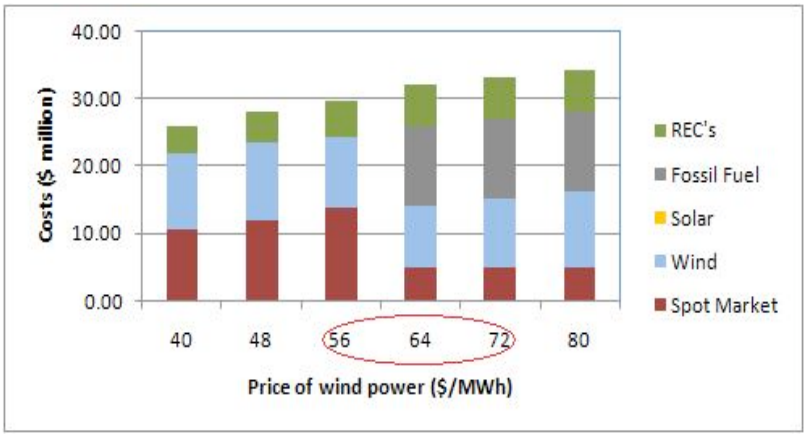


Figure 5: REC and hour-ahead purchasing costs from increasingly refined charging strategies.

3.4 Cost Sensitivity

Figure 6 presents the sensitivity of our results on various parameters which strongly affect the optimal solutions in our model. For each plot all problem parameters, except for the one being varied, are held fixed to their baseline values and the optimal supply mix is recalculated for each value of the varying parameter.



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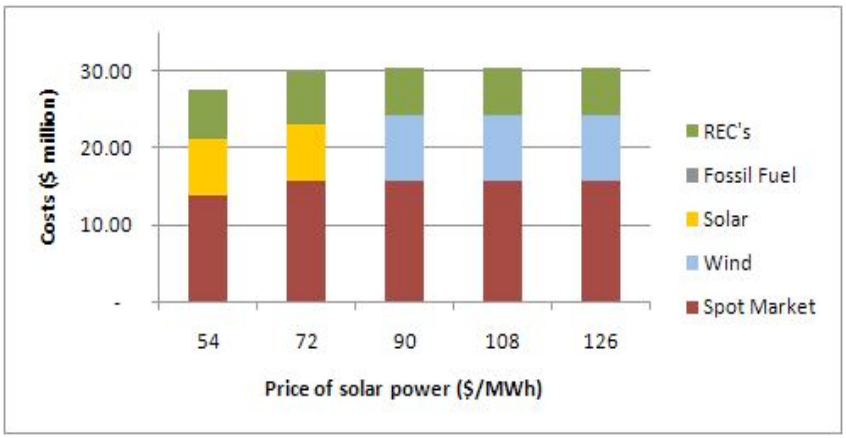

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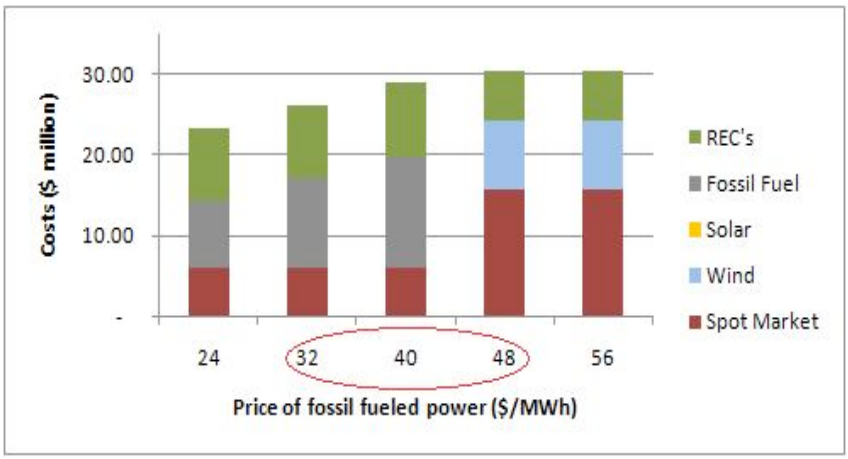

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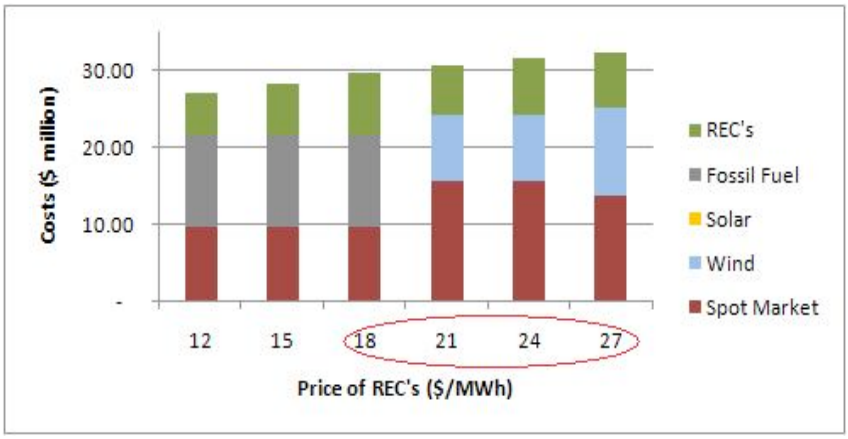

Figure 6: Sensitivity of optimal contract on energy prices. From top to bottom: cost breakdown for varying wind power, solar power, fossil fuel power and REC prices.

The upper bar diagram shows that overall supply costs are quite sensitive to wind power prices. For low prices wind power is the optimal choice, while as price increases it is optimal to include fossil fuels in the mix. Including fossil fuels suppresses hour-ahead market costs but boosts REC costs. We can conclude that for a reasonable range of wind

power prices wind power is cost competitive with fossil fuel power supply in the supply mix of a carbon neutral EV service provider.

From the second bar diagram we observe that solar power enters the optimal supply mix below $72/MWh for solar power generation. This is considerably less than the current cost of most solar power generation technologies. For higher prices of solar power, it is optimal to shift from solar to wind power contracts.

In the third bar diagram we observe that beyond a fossil fuel price of $44/MWh it is optimal to transition from fossil fuels to wind power. Again we observe that wind power is cost competitive with fossil fuels for a reasonable range of fossil fuel prices.

The fourth bar diagram highlights the tradeoff between fossil fuels and wind. For low REC prices it is profitable to purchase fossil fuel contracts and pay the deficit in RECs, but beyond $18/MWh the total expenditure in RECs warrants a complete crossover to wind power, and results in a boost of hour-ahead market purchases. Wind power appears to be cost competitive with fossil fuel generation for a reasonable range of REC prices.

4. Future work

The optimal vehicle charging problem described in section 2 presents a challenging optimal control problem and the simple charging rule which we have used can be significantly improved. In particular, various suboptimal dynamic programming techniques can be fruitfully applied as mentioned in section 2.1.

The analysis presented above adopts the point of view of the vehicle service provider, however it is also interesting to address the economic incentives of renewable energy generators. By supplying power to deferrable loads renewable generators are able to enhance their capacity credit since their generation can be reliably absorbed by shifting the consumption patterns of flexible loads. However, renewable generators would reduce their energy revenues by selling their power to flexible customers at a reduced rate in order to incent their flexible behavior. Whether renewable generators are better off earning a higher capacity credit by selling discounted power to EVs, or by supplying power at the hour-ahead market with a reduced capacity credit strongly depends on the extent to which renewable supply is correlated with the market price of electricity. The greater the correlation between market prices and renewable power supply the weaker the incentive of renewable generators to enter an exclusive contract with a flexible load class.

The use of a unit commitment model can be used for assessing the impact of renewable energy and EV integration on the hour-ahead market of electricity and the impact of transmission constraints on system operations. Within a unit commitment model it will be possible to incorporate loads as a resource which mirrors the behavior of generation resources and examine the impact on system operation costs and reserve requirements.

Finally, it will be interesting to investigate the sensitivity of these results on the ability of the system operator to accurately forecast renewable power supply.

5. Conclusion

We have used solar and wind power supply models for the state of California and a simple driving pattern model for assessing the extent to which renewable power can be used for fueling electric vehicles. Solar and wind power supply seem to have complementary patterns, with wind power resulting in greater EV energy supply per installed MW. Both renewable energy sources are influenced significantly by seasonality with supply being greatest during the spring and lowest during the fall. By modulating the charging patterns of EVs we obtain a significant level of wind power utilization. For example, using 120 MW to charge 100,000 vehicles covers 59% of the EV energy demand while resulting in 90% utilization of wind power. In order to assess the economic competitiveness of renewable power we calculate the optimal supply portfolio of an EV service provider which has the option of supplying energy to vehicles either through renewable power supply contracts, fossil fuel supply contracts or the hour-ahead market, subject to the constraint of offsetting vehicle emissions. According to our baseline assumptions, the best choice for supplying electricity to 100,000 EVs is contracting for 60 MW of wind power. This is a conservative choice, whereby wind almost never exceeds EV demand, but only covers 31.2% of vehicle energy demand, with the resulting deficits purchased in the hour-ahead market. Solar power becomes an economical option only below $72/MWh, which is significantly below the cost of most existing solar technologies. In contrast, wind power is economically competitive with fossil fuel generators at a reasonable range of wind power, fossil fuel power and REC prices. Careful charging strategies can increase the amount of wind energy that is economically absorbed by EVs, and can result in $8 million of annual cost savings.

Acknowledgements

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Biographies

Anthony Papavasiliou is a third year PhD student in the department of Industrial Engineering and Operations Research at UC Berkeley. He received a BS degree in Electrical Engineering and Computer Science from the National Technical University of Athens, Greece. Anthony has interned at XEROX PARC, has received two honorable mentions from the Link Foundation Energy Program, and has received the 2009 Sustainable Products and Solutions Program Fellowship, the 2008 Energy and Environmental Innovation award and the 2008 Information Technology for Society award at UC Berkeley for his work on wind power integration and demand response.

Ikhlaq Sidhu is appointed in the Department of Industrial Engineering and Operations Research at UC Berkeley. Professor Sidhu is an authority on the process of innovation and technology management, with a prolific background as an inventor and executive in the telecommunications and networking industry. He is the founding director of UC Berkeley's Center for Entrepreneurship & Technology, founding faculty director for the Berkeley-Tsinghua Global Innovation Center, and Co-chair of UC Berkeley's Management of Technology Program. Within industry, he has held senior executive and technology leadership positions at U.S. Robotics Corporation, 3Com Corporation, and Cambia Networks. He was awarded 3Com's "Inventor of the Year" award in 1999, and has been granted over 50 US Patents in fundamental and broadly used areas of networking technology, IP telephony, and PDA functionality.

Shmuel Oren is Professor of Industrial Engineering and Operations Research at the University of California, Berkeley. He is the Berkeley site director of PSERC. He has published numerous articles on aspects of electricity market design and has been a consultant to various private and government organizations. He holds a BS and MS degree in Mechanical Engineering and Material Engineering from the Technion in Israel and he received a MS and PhD degree in Engineering Economic Systems in 1972 from Stanford. Dr. Oren is a fellow of INFORMS and a fellow of the IEEEs professor of IEOR.

Phil Kaminsky is an associate professor in the Industrial Engineering and Operations Research Department at UC Berkeley. His current research focuses on the analysis and development of robust and efficient techniques for the design and operation of logistics systems and supply chains. He is a co-author of "Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies" (McGraw-Hill, 1999, 2003), which won the Book-of-the-Year Award and Outstanding IIE Publication Award in 2000, and is co-author of "Managing the Supply Chain: The Definitive Guide for the Business Professional" (McGraw-Hill, 2004).