An Assessment of the Price Impacts of Electric Vehicles on the PJM Market

A joint study by PJM and Better Place

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I. INTRODUCTION

A widespread concern of electric vehicles (EVs) is that the added load such vehicles place on the electric power system will reduce stability, reliability, and cost-efficiency of the overall system. PJM and Better Place performed a study to estimate the market and electricity price impacts of 1 million EVs in PJM's control area. This study considered a distribution of 1 million EVs in the Washington-Baltimore Metropolitan Area and modeled the impact of charging the EV batteries in three scenarios: unmanaged charging, consumer-price-incentivized charging, and managed charging via a Central Network Operator (CNO). Each charging scenario includes local charging intelligence, the details of which are outlined in later sections. CNOs are distinguished by the presence of communication systems and a centralized network control center. We developed a consumer transportation model to predict hourly energy requirements of EVs and generate load inputs for PJM's nodal pricing market model. PJM ran market model simulations based on the outputs of the energy demand model for each of the three scenarios in five different weeks of the year. The results show that managed EV charging, compared to the other scenarios, substantially dampens the increase in energy production cost, Locational Marginal Prices (LMPs), and therefore the wholesale energy cost. This outcome implies that, of the three scenarios tested, the CNO model is the most cost-effective way to integrate massively deployed EVs with the electrical grid. The study demonstrates that CNOs are able to achieve this cost-advantage by virtue of their ability to forecast EV demand and to quickly adjust and reschedule EV demand according to real-time LMPs. Finally, we show that networked charging of EVs can benefit the electric power system by providing fast responding ancillary services. This analysis was carried out using Better Place's network models and experience as a CNO. However, the results of this study are intended to be extensible to any CNO that provides managed EV charging.

II. EXECUTIVE SUMMARY

- Better Place and PJM have shown in this study that managed charging through a CNO using real-time LMPs has the ability to substantially reduce EV grid impacts compared to charging schemes without a CNO.
- The CNO managed charging algorithm charges batteries based on a number of criteria: *a)* energy needed for next planned trip; *b)* time until energy is known or predicted to be needed; *c)* current battery state-of-charge; *d)* time of day; *e)* forecasted LMPs; and *f)* real-time LMPs. For CNO managed charging of 1 million EVs using real-time LMPs, we have shown that PJM will save $350

million annually on cost increases due to the added load of EVs, compared to the unmanaged charging scenario. This represents a 45% reduction in additional energy costs that would otherwise be incurred from ad hoc charging of EVs by consumers.

- The scenario with time of use (TOU) pricing reflects a distributed intelligence platform with a fixed pricing schedule that does not have a CNO. The two-tier pricing scenario, modeled on the pilot EV tariff developed by Southern California Edison[1] (SCE) for EV charging, was evaluated and found to provide no significant benefit. Compared to the unmanaged charging scenario, there was actually an additional cost of $32 million (4%) annually.
- Wholesale energy cost was chosen as the primary metric for grid impacts because of its physical significance and transparency on the power system. Wholesale energy costs, which are calculated using nodal LMPs, include the costs of energy, congestion, and losses, meaning that any cost from generation to nearest transmission substation is reflected by LMPs. We therefore believe that any credible charging scheme that aims to reduce grid impacts will result in decreased wholesale energy costs.

III. MODEL OVERVIEW

We built a time-based model from the bottom-up to highlight the differences between charging schemes on an hour-by-hour basis. The model was written in Octave, which is an open-source MATLAB-like numerical programming language. The model generates trips for more than 1M vehicles based on census tract level employment and transportation data. Each vehicle has unique driving patterns and charging behavior. The simulation monitors each vehicle's location every 15 minutes and measures distance driven, the battery state of charge (SOC), and the EV charging facilities visited.

The model evaluates three different charging scenarios during five weeks in 2009-2010. The charging scenarios chosen include an Unmanaged Charging Scenario ("Unmanaged Scenario"), a Time-of-Use (TOU) Price Response Scenario ("TOU Scenario"), and the CNO Managed Charging Scenario ("CNO Scenario"). The Unmanaged Scenario reflects conventional charging where batteries begin charging as soon as they are plugged in. The TOU Scenario evaluates EV impact while charging according a two-tier TOU pricing scheme, modeled after SCE's EV-1 Charge Plan. Finally, the CNO Scenario extends the TOU Scenario to incorporate control by a CNO with real-time LMPs. We

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[1] http://www.sce.com/CustomerService/rates/residential/electric-vehicles.htm

evaluated weeks in October 2009, February 2010, April 2010, June 2010 and July 2010, which represents a typical fall, winter, spring, summer, and a hot summer week, respectively.

Numerous types of EV charging facilities are included in the model. Level 2[2] charge spots are modeled at residences and work places. Battery Switching Stations (BSS) are modeled along major thoroughfares for range extension in the CNO Scenario. Quick charging stations are substituted for BSS in the Unmanaged and TOU Scenarios. While BSS are currently unique to Better Place, the model treats the various range extension methods as technology neutral. The only difference between a BSS and a quick charger in this model is that the BSS's energy demand can be smoothed out over the day, reflecting the ability of a CNO to manage its charging infrastructure. Quick charging loads appear in the energy model when the vehicles demand their service, reflecting the lack of energy management in an unmanaged or TOU price responsive charging scenario.

Census tract centroids are used as a proxy for charge spot distribution and grid mapping. Charge spot and BSS loads are mapped to various substations within the metropolitan area. These loads are then processed by PJM's dispatch and market model that determines any reliability constraints and calculates changes in LMPs. The additional EV load is balanced by supply resources using a least production cost optimization.

IV. INFRASTRUCTURE DEPLOYMENT

A. Distribution of EVs

EVs were distributed by census tract by Median Household Income (MHI), our proxy for affluence, according to the US Census 2000[3]. We assumed EV penetration to be constant in regions with MHIs exceeding \$75k. To define EV penetration outside of such high MHI regions, we used an arbitrarily-defined parabolic cutoff. The blue shaded area in Figure 1a shows the distribution as a function of MHI overlaid upon a histogram of census tract income. The resulting EV penetration in the census tracts is shown in Figure 1b.

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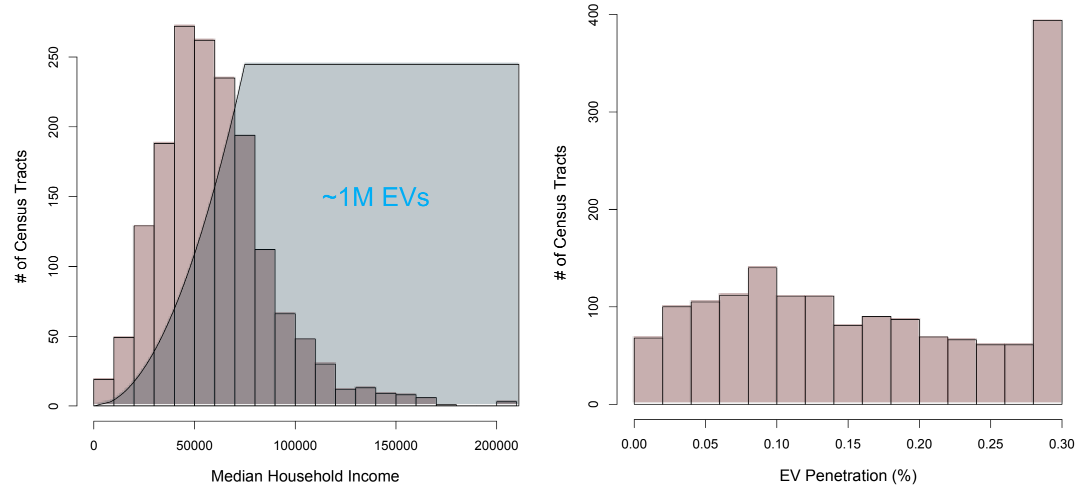
[2] Level 2 charge spots are assumed to be 240V 16amp connections

[3] http://www.census.gov/main/www/cen2000.html



(a) EV Distribution versus "Affluence"

(b) Resulting EV Penetration

Figure 1: EV Distribution and Penetration. The blue shared area in Figure 1a shows EV distribution versus affluence. A histogram of EV penetration is shown in Figure 1b. Note that due to the flat distribution curve above a median income of $75k, the % penetration is constant throughout most of the census tracts.

B. Distribution of Charge Spots (CS)

Every EV owner has a home CS. There are no public CS, such as at malls, food stores, etc. All EV owners who live ≥ 20 mi from work receive a work CS. We assumed a commuter to non-commuter EV ratio of 2:1.

C. Battery Switch Stations (BSS)

The placement and location of BSS took into account several factors including major transportation intersections, along routes of interest, and to provide reasonable spatial coverage. BSS sites were chosen independent of home and work CS locations. Prior Better Place transportation network analyses provided indicative coverage ratios that translated to approximately 250 BSS with a total of 500 car lanes. The placements of BSS infrastructure inside the study region are shown in Figure 2. BSS sizing was estimated based on AADT data of Maryland[4], however, due to a lack of data elsewhere in a convenient format, stations in Virginia and West Virginia were interpolated from the simulated transit data from our transportation model.

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[4] 2001-2009 AADT Shapefile data. Email correspondence with the Maryland Highway Information Services Division <http://www.marylandroads.com/Index.aspx?PageId=251>

In the Unmanaged and TOU Scenarios, we model the BSS as clusters of quick-charging stations. The infrastructure placement and sizing was the same but the quick-chargers have different power consumption properties and impacts on transportation, which are discussed later. We distinguish BSS from these clusters of quick-chargers by calling them Battery Quick Chargers ("BQCs").

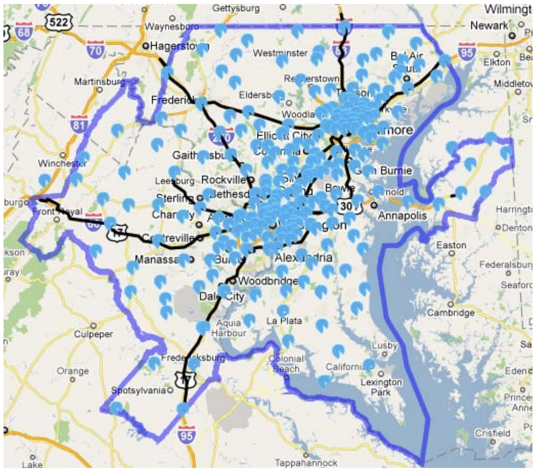

Figure 2: Placement of BSS Infrastructure - Placement of BSS infrastructure is shown inside the Washington-Baltimore Metropolitan Area are shown. Each Better Place logo represents a BSS. A BSS may range from 1-5 lanes with a total network size of approximately 500 lanes.

V. CONVENTIONAL URBAN TRANSPORTATION MODELING

A. Trip Generation

1) Commuting Trips: We assume that all workers have typical driving patterns. Workers are assigned to arrive to work at 9am ± 0.5σ hours and stay at work for 8.5 ± 0.75σ hours. In this simulation, commuter vehicles are not used during work hours. For the evening commute home and for post-work trips, we use probabilistic distributions described in the Trip Distribution section.

2) Non-Commuting Trips: Trips are generalized as home (H), work (W), or other (O). For non-commuters, the possibilities are combinations of HH, HO, OO, OH. For workers, the possibilities include work, such that we could have 9 combinations of H, W, O, however, we exclude trips that originate at work until the end of the work day. WW trips are always excluded for simplicity. Data for each of the 9 combinations was extracted from the NHTS chained trip dataset[5]. Note that the raw chained trip data only includes subjects that took trips, so the trips/day/pp is naturally higher than would be observed in the population. For this reason, we scaled the relative probabilities of taking trips to target 3.8 trips/day and the result can be seen in Figure 3. For reference, according to the Highlights of the 2001 National Household Transportation Survey[6], individuals averaged about 4 trips/day.

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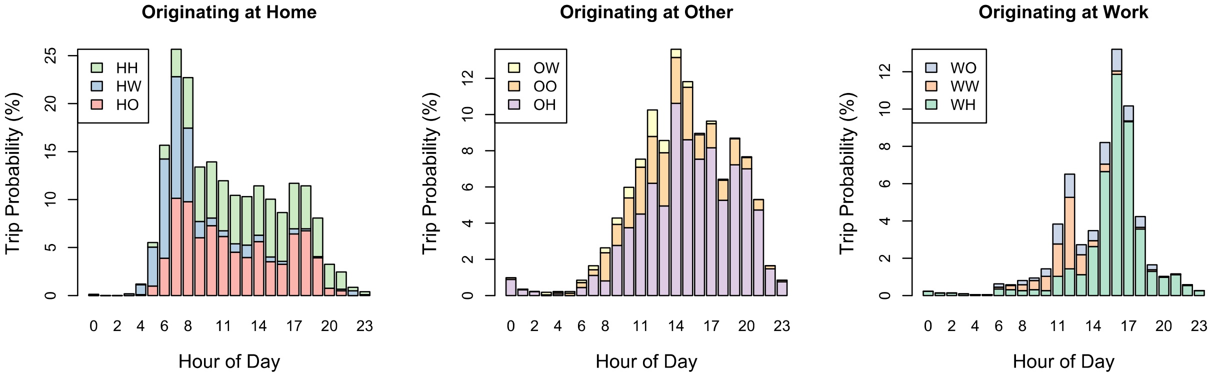
[5] http://nhts.ornl.gov/2001/download/TripChaining.zip

[6] http://www.bts.gov/publications/highlights_of_the_2001_national_household_travel_survey/

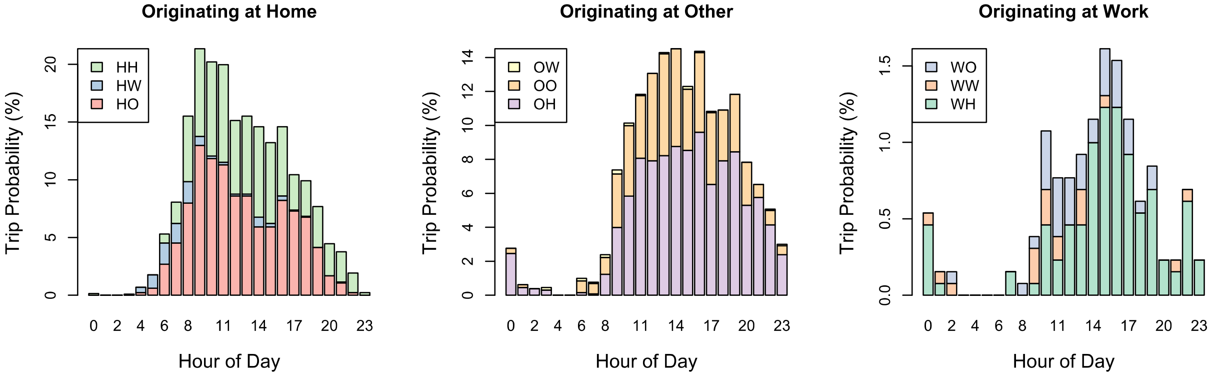


Originating at Home

Originating at Other

Originating at Work

(a) Monday Trips



Originating at Home

Originating at Other

Originating at Work

(b) Sunday Trips

Figure 3: Chained Trip Probabilities - Hourly probabilities of taking a given type of trip. Probabilities in 15-minute intervals are smaller since the probability of taking a trip depends on the time interval. Trips originating at work are excluded until the work day is over. WW trips are always excluded. Note that we use data from several states on the East Coast including MD, VA, WV, NJ, CT, MA, and DE to increase sample size.

B. Trip Distribution and Mode Choice

1) Commuting Trips: Commuter trips to work were distributed based on Cornell's OnTheMap (OTM) dataset[7]. The OTM dataset provides data that links census tracts by the number of people that live in one tract and work in another tract. This data does not include modes of transportation or any other information about commuting behavior. To estimate EVs used for commuting, we scaled the flow network using US Census 2000 transit mode data[8]. The transit mode data is used to estimate a driving

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[7] http://www.vrdc.cornell.edu/onthemap

[8] Table P30 from US Census 2000, "Means of Transportation to Work for Workers 16 Years and Older"

ratio for commuters. This was calculated as the ratio of occupants in SOVs and HOVs out of the all modes combined. The core assumptions are:

- Aggregated commuting behaviors/statistics can be applied flatly to the census tract
- Ownership of EVs is determined by affluence rather than whether or not it may be used for commuting

With that, we calculated the flow of EVs, F_{ij}^{EVs}, from tract *i* to *j*, in the following steps/multiplications:

1. How many links are formed by workers between two census tracts (F_{ij}^{OTM})
2. How likely are they to drive? ($\times\ R_i^{drive}$)
3. Given they are driving, how likely are they to drive an EV? ($\times\ N_i^{EVs} / N_i^{tot}$)

The resulting formula for F_{ij}^{EVs} is given below. Note that the network was scaled to achieve a commuter to non-commuter EV ratio of 2:1.

$$F_{ij}^{EVs} = F_{ij}^{OTM} \times R_i^{drive} \times \frac{N_i^{EVs}}{N_i^{tot}}$$

2) Non-Commuting Trips: For non-work related trips, we distributed trips according to a gravity model[9] with a somewhat arbitrary (but used elsewhere) mass function. The function has 3 parameters: emissivity *(η)*, attractiveness *(α)*, and distance *(d)*. Technically, emissivity is not important because our trip "emissions" are bundled into the trip generation probabilities and are assumed to be the same for all people in all tracts. The parameter would be important, however, if we were solving the system for flow.

As a proxy for attractiveness, we use OTM worker flow into a census tract. Although using worker-flow data to describe recreational drives, grocery store visits, or dentist appointments may not seem appropriate, it is fairly logical to think that consumers drive where others work.

In the formula below, T_{ij} describes the percentage of trips originating in census tract *i* to *j*. Note that the conventional use of the matrix, *T*, describes the number of unscaled trips within an entire network. We normalize *T* such that each row sums to 1. The distance factor is weighted more on weekdays than weekends since people tend to drive greater distances on weekends. The exponents of 2.6 and 2.15 were found by tuning the model to achieve roughly 12k mi/yr, 3.8 trips/pp/day, and have a weekly VMT profiles that correspond to the NHTS chained trip data in the selected region. As mentioned previously, since the chained trip data includes only trips taken, the weekly VMTs as calculated by the chained trip

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[9] http://en.wikipedia.org/wiki/Trip distribution#Gravity Model

data is over estimated and we scaled down these numbers down about 30% to yield 12k mi/yr in that dataset.

$$\text{on weekdays: } T_{ij} = \frac{\eta^{0.5}\alpha^{0.5}}{d^{2.6}} \text{ and on weekends: } T_{ij} = \frac{\eta^{0.5}\alpha^{0.5}}{d^{2.15}}$$

D. Route Assignment

There are two classes of route assignments, either along pre-determined routes or by drawing straight lines between locations. Pre-determined commuter routes for 165k location pairs were calculated using an open-source mapping package called Gosmore. Gosmore returns a series of waypoints (GPS coordinates), ETA in seconds, and some additional information about roads and intersections. We use the Great Circle Distance formula[10] to calculate the distance between all of the waypoints and then sum them to find the distance along the route (Gosmore does not do this automatically). We also filtered out routes shorter than 5 mi to increase computational speed and reduce memory usage. Those routes > 5mi are overlaid on top of one another (scaled by their F_{ij}^{EVs} values) and shown in Figure 4 on a logarithmic scale for detail.

We compared some values with Google Maps[11] where the distance calculations were identical, however, driving times were systematically 20% faster than Google's predictions. We corrected the driving times to match those calculated in Google Maps. Finally, with regards to routing, note that since the time-step is 15 minutes, drivers appear to "jump" from one location to another without following the highways exactly. This modeled behavior has some impact on the stations that drivers use to extend their range, but does not affect energy consumption.

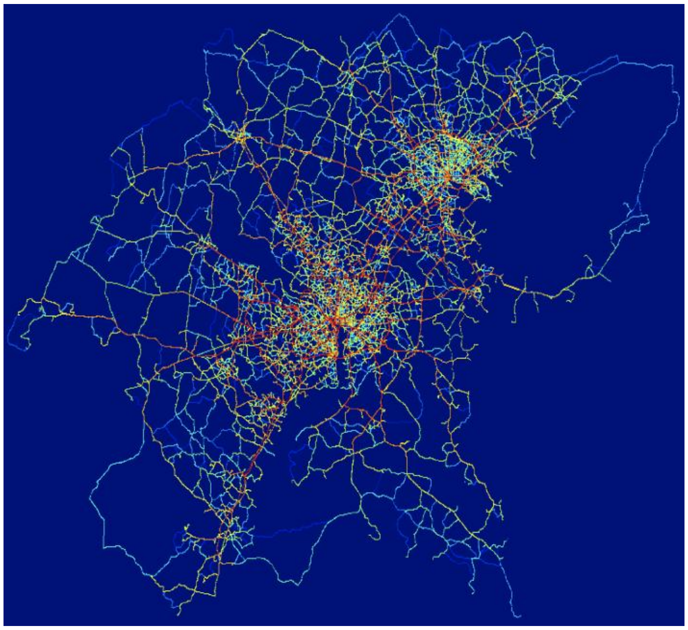

Figure 4: Trip Route Assignments - Route assignments for commuter trips > 5 mi are shown for visualization. Shorter and non-work related trips are represented by straight lines and are not shown here.

For non-workers and short commuter routes, we draw routes along straight lines. We convert orthodromic distance (direct distance along a line) to distance along a route by using a factor of 1.3

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[10] http://en.wikipedia.org/wiki/Great-circle distance

[11] http://maps.google.com

that we determined by linear regression of orthodromic distance versus the actual route distances from Gosmore. We assume an average velocity of 30 mph for all routes without pre-determined directions and driving times.

VI. CHARGING SCENARIO BEHAVIOR

A vehicle cannot charge or be controlled unless it is plugged in—we assume all drivers plug in diligently whenever they complete a trip near a CS. Although plug in behavior will certainly affect controllability and load dynamics, we made this behavioral assumption to reduce complexity.

A. Charge Spots

1) Unmanaged Scenario: The charger charges at 6.6kW until the battery is full. There are no physical or economic constraints placed on the charging. There is no CNO.

2) CNO Scenario: The CNO Scenario represents charging by a CNO that is attempting to optimize the time and location of energy delivery according to driver needs and electricity grid constraints. To simulate an EV aggregator's network operations center, the CNO Scenario assumes knowledge of 20% of trips under 20 miles and 80% of trips over 20 miles. It is therefore necessary to ensure that a minimum level of charging occurs to ensure that there is enough energy in a battery for both planned and unplanned trips. The charging algorithm charges batteries probabilistically based on a number of criteria: *a)* energy needed for next planned trip; *b)* time until energy is known or predicted to be needed; *c)* current SOC; *d)* time of day; *e)* forecasted LMPs; and *f)* real-time LMPs. Forecasted LMPs are constructed from LMPs on adjacent days. Probabilistic charging is implemented to avoid simultaneous charging with all actors acting on the same price signal. That said, although prices may be low, the CNO will not charge all vehicles at once.

In general, the CNO aims to: 1) reduce the cost of its own electricity usage; 2) eliminate load spikes; 3) charge all vehicles by morning; and 4) charge commuter vehicles with charge spots before leaving work. Two CNO charging profiles were developed to respond to seasonal variations in load within PJM territory. We classify these two profiles as summer and winter loads as those seasons best define the load characteristics. Summer load profiles are generally sinusoidal with a single daily peak. Winter profiles have loads with two peaks due to heating and lighting loads in the morning and evening. Summer charging profiles were applied for the June, July, April, and October weeks even though April and October begin to show signs of morning and evening peaks. February was the only week with the winter CNO profile applied. Overnight charging during the summer load profiles starts at approximately 8pm and stretches as late as 8am, and varies primarily by when vehicles leave in the morning. In the winter, overnight charging avoids the morning and evening peaks by starting later and ending earlier (around 11pm-6am). We must emphasize, however, that the driving patterns were kept constant between seasons. These details will be explained further in Section VII on the integration of the energy model with PJM.

3) TOU Scenario: The TOU scenario reflects a distributed intelligence platform with a fixed pricing schedule that does not have a CNO. The TOU Scenario is similar to the CNO Scenario, with the two main differences being the price forecasts and the exclusion of real-time locational pricing. "Forecasted prices" in the TOU Scenario are pre-determined as the two-tiered TOU prices from SCE, described in detail below. It is important to highlight here that the distributed intelligence platform has the same objective functions as CNO and it assumes all of the same trip knowledge as in the CNO Scenario, but its functionalities are limited in that it has a fixed pricing schedule and knowledge of only its own energy needs.

The two-tiered TOU pricing schedule was adapted from Southern California Edison's "Schedule TOU-EV-1, Domestic Time-of-Use Electric Vehicle Charging".[12] The schedule provides two-tiered pricing for EVs with a dedicated meter for On- and Off-Peak hours. According to the website[13] as of February 15, 2011, On-Peak hours are 12:00-21:00 daily (including weekends) and Off-Peak hours are all other hours. Off-Peak prices are approximately \$60.17/MWh and On-Peak prices from Summer and Winter seasons were averaged to \$143.45/MWh. We assumed that 70% of customers would be sensitive to this pricing schedule; the remaining 30% charge as they would in the Unmanaged Scenario.

B. Battery Switch Stations

Battery Switch Stations are modeled in two distinct ways. Formal Better Place BSS only exist in the CNO Scenario. For the Unmanaged and TOU Scenarios, we model the BSS as a cluster of Quick-Chargers ("BQCs"). The two BSS models are not equivalent in terms of power consumption or impact on transportation dynamics. In order to make reasonable comparisons between the scenarios, however, it was necessarily to keep driving patterns identical between each of the scenarios. Thus, vehicles visiting a BSS receive a full battery instantaneously and vehicles visiting a BQC receive an 80% charge

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[12] http://www.sce.com/NR/sc3/tm2/pdf/ce114-12.pdf

[13] http://www.sce.com/CustomerService/rates/residential/electric-vehicles.htm

instantaneously. In reality, a battery switch will take approximately 3 minutes where a quick charge could take up to 30 minutes. To model the energy consumption, empty batteries in a BSS continue to charge after the vehicle leaves the station—just as it would occur in an actual station. This charging occurs at a rate of 24kW up to a 100% SOC. Since charging at a BQC would otherwise impact transportation patterns, we modeled a phantom load that draws energy at a rate of 40kW up to an 80% SOC after the vehicle leaves the BQC site. Although this quick-charging behavior is unrealistic, it is a generous portrayal because in real energy terms, an 80% charge that is equivalent in service time to a 3-minute battery switch would require a phantom load of 400kW for 3 minutes. This behavior is more closely related to that of battery fast-chargers, but we did not model the BQCs as such because they are not commercially available and the high power, short duration loads would not be represented properly with our 15-minute time-steps.

Routing of an EV driver to a BSS has intelligence in the CNO Scenario. As before, in order to keep the driving patterns identical among scenarios, there is no time or energy penalty for travel to a BSS or a BQC. Routing intelligence will be discussed further in scenario specifics below.

Battery switch stations were sized as previously discussed (see Section IV-C). Along a route, there is preference to switch at a large station, as it is more likely a given vehicle is on a main artery. Switching typically occurs when a subject is driving and the battery's SOC goes below 10-16%, a comfort level that is pre-determined for a particular EV owner based on a uniform distribution. Standard switch behavior is therefore akin to filling up only when the gas tank is around 1/8 full. A small portion of switches do occur at higher SOCs. Vehicles will not switch if their destination has a CS (work or home) and they can reach their destination before depleting the battery.

1) Unmanaged and TOU Scenarios: Routing of a driver to a BQC is performed using only BQC size and distance to the driver as inputs. Whenever an EV needs to visit a BQC, it calculates a likelihood that it may charge at a given BQC station using the formula below, where d_k is the distance to the BSS from the current location of the vehicle and N_k is the number of chargers at each BQC.

$$L_k^{BQC} = \frac{N_k}{d_k}$$

One of the stations with the top three likelihoods is chosen at random, weighted by their likelihoods. There are no checks or limits based on the number of supposed batteries, chargers, or lanes at a station.

Since the BQCs are clusters of quick-chargers, we assume that a driver will fill their battery only to get them to their next destination with a charger with a comfortable buffer.

2) CNO Scenario: In CNO Scenario, BSS availability and real-time nodal pricing information is available to the network operator to intelligently route a driver to a BSS based on a multitude of factors. We chose here to represent five different factors as inputs to the BSS routing algorithm: 1) forecasted prices; 2) real-time pricing; 3) BSS size; 4) BSS availability; and distance. Coefficients for factors are represented as: P_k^f for forecasted prices at BSS k, P_k^{RT} for real-time prices, number of lanes as N_k, availability as A_k, and distance as d_k. The relative likelihood that a station switches at a BSS is given by:

$$L_k^{BSS} = \frac{N_k}{d_k} \frac{1}{P_k^f P_k^{RT}} A_k$$

As in the Unmanaged and TOU Scenarios, one of the stations with the top three likelihoods is chosen at random, weighted by their likelihoods.

At the switch station, the batteries charge at a maximum rate of 1C, which is 24 kW for a 24 kWh battery, and charge until full.

VII. INTEGRATION WITH PJM DISPATCH AND MARKET MODEL

The workflow is composed of four layers shown in Figure 5: the Transportation Model, the Energy Load Model, the PJM Market Model, and Impact Assessment. Charge spot loads from the Energy Model were aggregated around census track centroids and then mapped to substations for the PJM Market Model; BSS loads were mapped directly to substations. In the Unmanaged Scenario, the energy model does not consider LMPs when charging. The TOU Scenario uses the fixed TOU pricing as an input into the Energy Model.

The most complex scenario is the CNO Scenario where the LMPs from the PJM Market Model feed back into the Energy Load Model. Ideally, this feedback step would occur in real- time so that we could adjust the load based on prices and driver needs in each time-interval. The two models, however, are not fully integrated and both currently run without any real-time communication. To simulate real-time pricing, LMPs from the unmanaged scenario are passed into the Energy Model of the CNO Scenario. Essentially, the first model iteration (i.e., the Unmanaged Scenario) determines an approximate pricing landscape with uncontrolled charging. The second model iteration, deemed the CNO Scenario, attempts to correct negative grid impacts observed in the Unmanaged Scenario. That said, we perform two iterations: unmanaged and then managed. Unfortunately, in just those two iterations, it is unknown how any new perturbations will affect LMPs. If the models were linked in real-time, as they would be in reality with real-time nodal LMPs, we would immediately observe the impact of our load on the network and could respond accordingly. Therefore, we assume that a sophisticated CNO would be better at protecting against LMP impacts in real-world conditions.

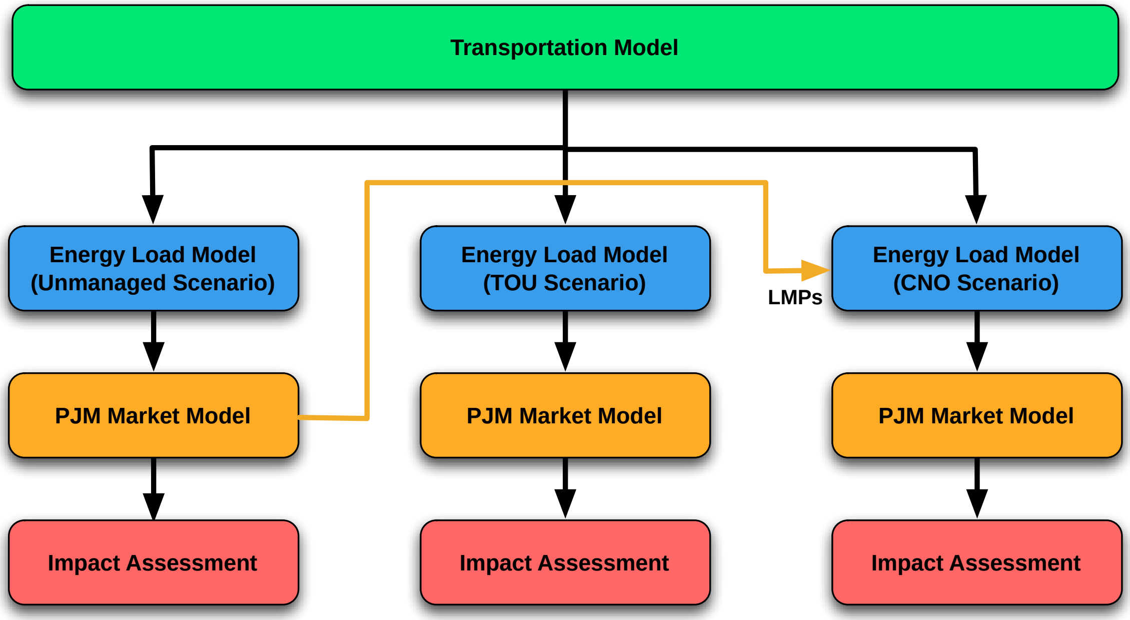

Figure 5: Workflow Diagram for Better Place and PJM Model Integration - The transportation model is fixed for all scenarios. The output of the Unmanaged Scenario's PJM Market Model is used as an input into the CNO Scenario's Energy Load Model.

VIII. PJM METHODOLOGY

A. Market and Dispatch Model

Once the physical locations of the Charge Spots and Battery Switch Stations were determined, the additional load needed to be represented in the bulk electric system model. These locations were matched to distribution substations by nearest distance, and EV demand was assigned proportionally to the distribution load transformers at those stations. Each distribution transformer is a point of withdraw from the transmission network, and as such, has a distinct locational marginal price (LMP). LMPs are sensitive to supply composition, transmission constraints, and energy losses incurred to serve load.

For each of the representative weeks, PJM executed security-constrained economic dispatch simulations using historical power flow models combined with market offer data. For the current study, the future possible changes of generation and transmission does not include in the simulation model. PJM's software optimizes the balance of energy supply and demand to satisfy all transmission flow limits with a least production cost algorithm. Electricity is a commodity that is cost-prohibitive to store at bulk levels, therefore it must be generated at the same rate at which it is consumed. Because the introduction of EV charging facilities increase the demand for electricity, the increase must be matched by increased supply. PJM's market dispatches the least cost generation to meet real-time demand, and ex-post pricing sets the locational price that demand pays for energy delivered. For each week, PJM executed a base case with no load adjustments to act as a reference for Better Place's load models.

Using time-series EV load data supplied by Better Place, PJM incremented the nodal load levels and executed additional simulations for sensitivity analysis. Each day's simulation generated new unit commitment solutions at a 30-minute time-step, such that all power balances were maintained. The simulation was bound against a generic list of transmission limits plus constraints that were active in the historical week. PJM executed optimized power flow dispatch simulations for the Unmanaged, TOU, and CNO scenarios. The simulations produced: *a)* new unit commitments for all generators to meet the adjusted load, *b)* nodal LMPs representing the price of energy at each generator and load, *c)* while considering costs due to transmission congestion and losses as energy is transferred within PJM and on the bulk power grid.

The optimization conducted by the simulation program minimizes bid production costs while ensuring the high-voltage electricity grid's reliability. LMP is more volatile than production cost as LMP capture the fluctuation of bid production cost changes in real-time. Production costs consider only committed units, while LMP are sensitive to the price and/or cost of marginal generator units.

B. Week Selection

The four weeks were selected to present four seasons over fall of 2009 to summer of 2010, since they had typical weather data and moderate transmission constraints. One week with high load was picked up for the study to show what impact will be by adding EV demand when the electrical grid had already close to its peak consumption.

Besides these general criteria, some abnormal results were screened out because of limitations in the simulation program. As mentioned in the previous section, LMP is not part of the optimization function of simulation program, which occasionally led to inconsistent behavior and atypical results between production and wholesale energy costs. For example, added EV load on the electrical system always causes the energy production cost to increase, however, in some rare circumstances it induced lower LMP across the PJM network.

IX. METRIC FOR IMPACT ASSESSMENT

The metric for "electric vehicle grid impacts" was chosen to be the increase in wholesale energy cost and electricity bid production cost as a result of adding loads within the network. Electricity bid production cost is minimized (and output) directly in the PJM Dispatch and Market Model. LMP changes were calculated weekly from half-hourly loads and LMPs across all n nodes:

$$\text{Impact on Wholesale Energy Costs} = \frac{1}{2}\sum_{i=1}^{n} \mathrm{Load}_i^{\mathrm{base}} \times \left(\mathrm{LMP}_i^{\mathrm{EVs}} - \mathrm{LMP}_i^{\mathrm{base}}\right)$$

As the model minimizes electricity costs for the CNO, we calculated the electricity costs by:

$$\text{CNO Electricity Costs} = \frac{1}{2}\sum_{i=1}^{n} \mathrm{LMP}_i^{\mathrm{EVs}} \times \left(\mathrm{Load}_i^{\mathrm{EVs}} - \mathrm{Load}_i^{\mathrm{base}}\right)$$

X. RESULTS

A. Model Behavior

We first observe the EV charging load characteristics in the Unmanaged Scenario, shown in Figure 6, where electric vehicle batteries charge until full as soon as they are plugged in. Although the model is run for a full week, we only show a three-day period from Thursday to Sunday for simplicity, which captures most of the weekly load dynamics. The two peaks in black represent the load when vehicles are charging at work in the morning and at home in the evening. Mid-day charging during the workweek is from mostly non-commuter vehicles. Note that the peak in the evening is larger than in the morning because only drivers who live more than 20 miles from work have a CS installed at work. Network load falls to zero overnight (3-6am) as all vehicles are charged by around 3am. Load-weighted average LMPs (in red) are overlaid to highlight that most charging occurs during the most expensive hours. The Unmanaged Scenario has no price feedback and charges blindly despite the high LMPs.

In the TOU Scenario, the electric vehicle charging algorithm factors in a two-tier TOU price signal, shown in red in Figure 7. EV network load in the TOU Scenario is shown in blue while the Unmanaged Scenario load is shown in the background in gray for comparison. The algorithm incorporates probabilistic charging that is intended to reduce aggregated peak loads while the price signal incentivizes individual vehicles to either defer or accelerate charging to reduce cost.

The new EV network load does show a peak load reduction from the Unmanaged Scenario of about 20%, however, the amount of load shifted overall is fairly small. Load shifting from on-peak hours to off-peak hours is about 7.8%. Note that the network load no longer drops to zero overnight and now maintains a baseload consumption of approximately 75MW. Although the EV Network pays the pre-determined TOU price, the grid is still impacted by the real-time LMP prices, which change as a result of the added load.

Network loads for the CNO Scenario are shown in blue in Figure 8 with the load-weighted real-time LMP price in red. The real-time LMPs are the price the EV Network pays for energy and it therefore serves as the price signal for the charging algorithm. Note that the charging algorithm is identical to the TOU Scenario with the exception of *1)* using forecasted LMP prices for a price signal rather than a two-tier signal, and *2)* an additional factor for Real-Time LMP price feedback. Peak charging loads in the CNO Scenario are consistently 30-70% less than the peaks in the Unmanaged Scenario. Additionally, the baseload consumption is as high as 175MW during the weekdays, but falls to as low as 125MW on weekends.

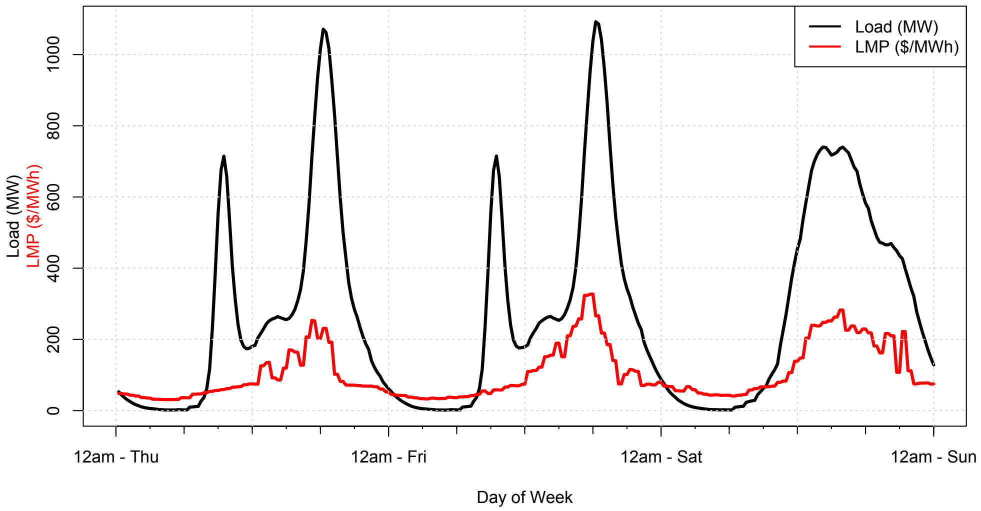

Figure 6: Charging Characteristics for the Unmanaged Scenario: The black line shows the EV Network load in the Unmanaged Scenario. The red line represents the EV Network load-weighted average real-time LMPs.

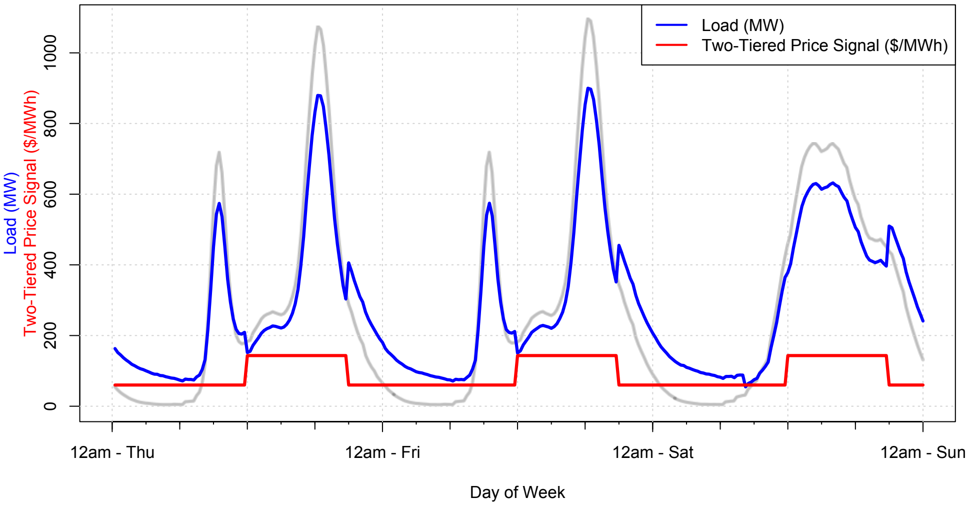

Figure 7: Charging Characteristics for TOU Scenario: The blue line shows the EV Network load in the TOU Scenario. The red line represents the TOU electricity prices. The Unmanaged Scenario load is shown in gray for reference.

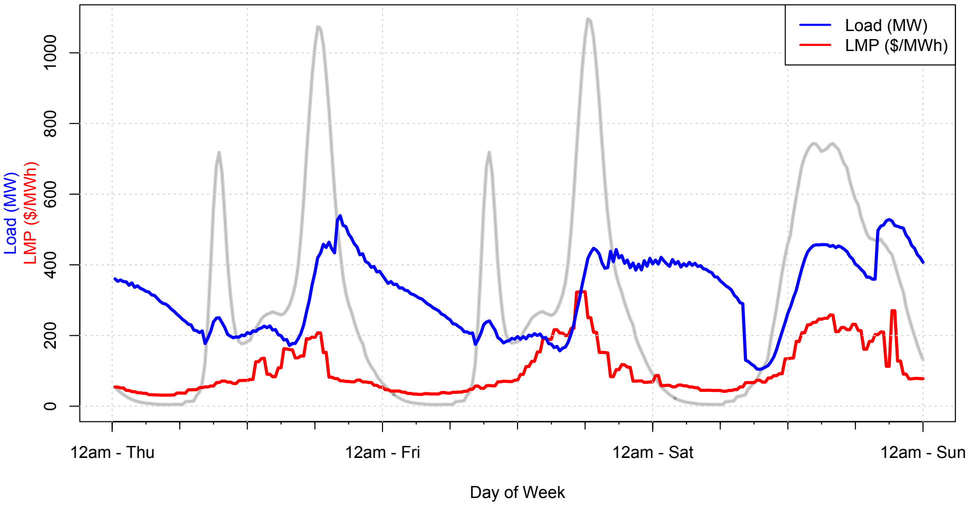

Figure 8: Charging Characteristics for CNO Scenario: The blue line shows the EV Network load in the Better Place Managed Charging Plan. The red line represents the EV Network load-weighted average electricity prices. Note that these LMPs have changed from the Unmanaged case because the LMPs are themselves different and the load has shifted. The Unmanaged Scenario load is shown in gray for reference.

B. Performance Metrics

Wholesale energy costs increases are shown for the five weeks analyzed in Table I. The CNO Scenario consistently outperforms the TOU Scenario in wholesale energy cost savings. Presuming that these five weeks represent an entire year with equal weightings, the CNO Scenario reduces load impact costs by 45%, which translates to an annual savings of $350 million. The TOU Scenario, however, increases the impact by 4%, costing an additional $32 million each year. The results from the TOU Scenario show savings in some weeks while additional costs are incurred in others. Recall that the TOU Scenario charging scheme does not incorporate the LMP prices used to calculate the costs of energy while the CNO Scenario scheme does.

As mentioned previously, the charging algorithm has two main objectives: reducing energy costs and reducing peak loads. The cost of electricity to the CNO therefore shows the performance of the objective function in each scenario, and is shown in Table II. The table is broken down into two pricing schemes, one based on real-time LMPs and the other based on two-tier TOU pricing. Note that the absolute costs from the TOU Pricing Scheme and the LMP Pricing Scheme are not directly comparable because the TOU Pricing Scheme is a retail rate while the LMP Pricing Scheme is a wholesale rate. However, percentage reductions between the two pricing schemes can be compared. For each pricing scheme, we calculate the savings relative to the unmanaged scenario as if those loads were subject, but not responsive, to the respective electricity prices in that pricing scheme.

For the TOU Scenario, we observe a modest performance in savings with only a 3.7% annual reduction in energy costs to the CNO. Recall that in Table I, the TOU Scenario increased the wholesale energy cost by 4%. For the LMP Pricing scheme, the CNO Scenario achieves a 22% savings annually ($37 million) for the cost of energy to the CNO. Thus, a savings of $37 million to the CNO is amplifies to a savings of $350 million in wholesale energy cost increases.

Electricity bid production cost increases are shown in Table III for each of the three scenarios. Savings in the TOU and CNO Scenarios are shown relative to the Unmanaged Scenario. On an annual basis, both the TOU and CNO Scenarios show a reductions in bid production cost increases, however, the TOU Scenario has a modest savings of 3% while the CNO Scenario has a savings of 23%. This indicates that the CNO Scenario represents a more efficient market.

	Unmanaged Scenario	**TOU Scenario**		**Managed Scenario**	
	$ Millions	*$ Millions*	*Savings (%)*	*$ Millions*	*Savings (%)*
February	6.41	10.15	-58%	5.21	19%
April	11.21	5.03	55%	1.36	88%
June	20.48	21.33	-4%	11.38	44%
July	30.83	28.97	6%	21.84	29%
October	6.68	13.24	-98%	2.13	68%
Annually	786.3	818.7	**-4%**	436.0	**45%**

Table I: Summary of Wholesale Energy Cost Increases as a Result of Added Electric Vehicle Load. Total wholesale energy cost increases are calculated for all three scenarios with percent savings scaled relative to the Unmanaged Scenario. These weeks are presumed to be representative of the entire year with equal weightings.

	TOU Pricing			LMP Pricing		
	Unmanaged Scenario	TOU Scenario		Unmanaged Scenario	Managed Scenario	
	$ Millions	*$ Millions*	*Savings (%)*	*$ Millions*	*$ Millions*	*Savings (%)*
February	5.62	5.38	4.3%	2.58	2.26	12%
April	5.60	5.42	3.3%	2.21	1.75	21%
June	5.78	5.53	4.4%	3.76	2.92	22%
July	5.75	5.60	2.7%	5.40	3.82	29%
October	5.68	5.47	3.8%	1.99	1.66	16%
Annually	295.8	284.9	**3.7%**	165.8	129.1	**22%**

Table II: Summary of Energy Costs to Aggregated EV Owners. Total energy costs are calculated for all three scenarios with percent savings scaled relative to the Unmanaged Scenario. These weeks are presumed to be representative of the entire year with equal weightings.

	Unmanaged Scenario	**TOU Scenario**		**Managed Scenario**	
	$ Millions	*$ Millions*	*Savings (%)*	*$ Millions*	*Savings (%)*
February	1.42	1.42	0.0%	1.23	13%
April	1.21	1.16	4.1%	0.93	23%
June	1.97	1.88	4.6%	1.48	25%
July	2.83	2.71	4.2%	1.97	30%
October	0.99	1.00	-1.0%	0.85	14%
Annually	87.6	85.0	**3.0%**	67.18	**23%**

Table III: Summary of Production cost Increases as a Result of Added Electric Vehicle Load. Total production cost is calculated for all three scenarios with percent savings scaled relative to the Unmanaged Scenario. These weeks are presumed to be representative of the entire year with equal weightings.

C. Flowgates and Constraints

The dispatch simulation monitors hundreds of transmission flowgates and other constraints on the PJM system. The flowgates and constraints may be on either physical lines or proxies for transmission boundaries and limitations. Additional constraints may be experienced in actual system operation due to variations in system operation, updated outage information, and contingencies. Among these constraints monitored by the simulation program, in the periods we assessed, there were about 10 binding constraints in weeks with low baseload and over 70 binding constraints in weeks with high baseload. A binding constraint means that the electrical flows of those constraints were either close to, or above, their normal flow limits. This will call more expensive generators to reverse the power flow and relieve the constraints. That expense is reflected in production cost and LMP.

Relative to system operation without EVs, the Unmanaged Scenario caused larger flows on those binding constraints already present on the network. This was especially problematic in the heavily constrained weeks of June and July, where power flow increased by 0.04% and 0.07%, respectively. The CNO Scenario, which attempted to avoid adding load when the system was heavily constrained, relieved power flows by 0.02% and 0.03%, respectively. Overall, total flows did not increase substantially after EV load was applied to the system, which indicated that the simulation program was able to appropriately dispatch generators to maintain and control system reliability.

D. Ancillary Services

Three types of ancillary services are assessed from the Better Place EV Network. Primary Reserves, or reserves used for Frequency Regulation (FR), will be provided from the BSS. Secondary and Tertiary Reserves (i.e. spinning and non-spinning reserves, respectively) will be provided by EVs.

1) Primary Reserves: BSS will be equipped with Voltage-Sourced Converter type inverters, or “bi-directional chargers”. BSS can provide regulating reserves by regulating charging (unidirectional frequency regulation) or by charging and discharging batteries. BSS were chosen to provide FR since they are point sources for load/generation and telemetry and metering equipment can easily be accessed and installed. Frequency regulation availability is based on a proprietary queuing and operations model that assumes vehicle arrivals at a BSS follow a Poisson arrival process based on the expected arrivals at a BSS that is calculated from the simulation data. Market capacity offerings are calculated to meet ≥ 95% while impacting subscriber SLAs by ≤ 1%.

Primary frequency regulation reserve capacity across the entire BSS network is shown in Figure 9.

The average capacity factor for the BSS network is fairly high at approximately 71%. This is the direct result of fairly low BSS utilization as two-thirds of the electric vehicles are commuter vehicles. Additionally, from the BSS availability, it is clear that the BSS network is more appropriately sized to serve weekend traffic rather than weekday traffic.

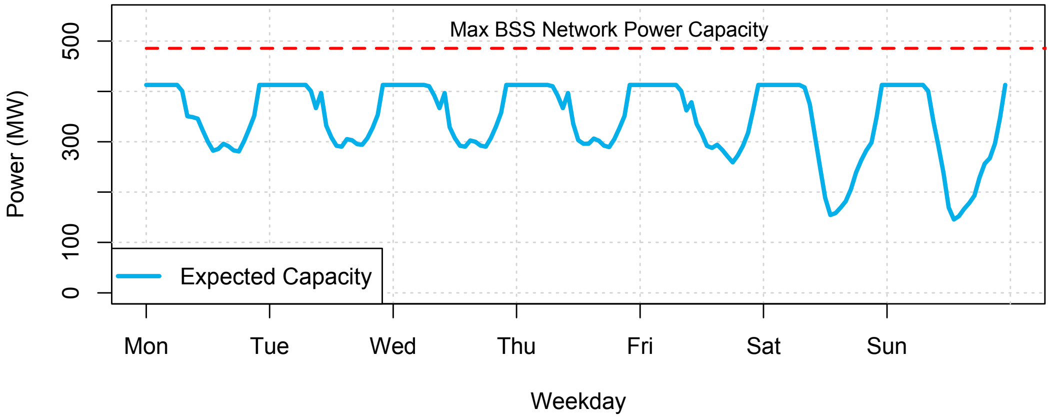

Figure 9: BSS Network Primary Frequency Regulation Reserves: Average frequency regulation reserve capacity from the Better Place BSS Network are shown on an hourly basis for a week. The Max BSS Network Power Capacity is given as the total collective power with all batteries in BSS connected at 48 kW.

2) Secondary Reserves: Secondary reserves from EVs are defined and calculated here as reserves available instantaneously for up to a 30-minute production/consumption commitment at full rated power. V2G capabilities are not required for negative secondary reserves (accelerated charging) but are required for positive secondary reserves as batteries are discharged.

The secondary reserves are highly predictable on a day-to-day basis, but availability may vary substantially among days and seasons. Vehicles providing secondary reserves face both a power and an energy limitation. The power limitation is simply the connection size, assumed to be 6.6kW in this report. Energy limitations are based on a 30- minute production or consumption period that does not deplete a battery below 40% or fill a battery above 100%. The power and energy limitations for providing 30-minute spinning reserve service are shown in Figure 10. Note that charging or discharging a battery for 30 minutes at 6.6kW only alters the battery SOC by 14% and therefore has a minimal impact on operations. This can be visualized further in Figure 10, where it is clear that energy limitations (in blue) for positive reserve are never as constraining as the power limitation (in red). Negative spinning reserves (in cyan), however, become the limiting factor from approximately 4-8am when batteries are nearly full. Aggregated secondary reserve availability, shown in Figure 11, is simply calculated as the minimum of either power or energy availability that the network can provide.

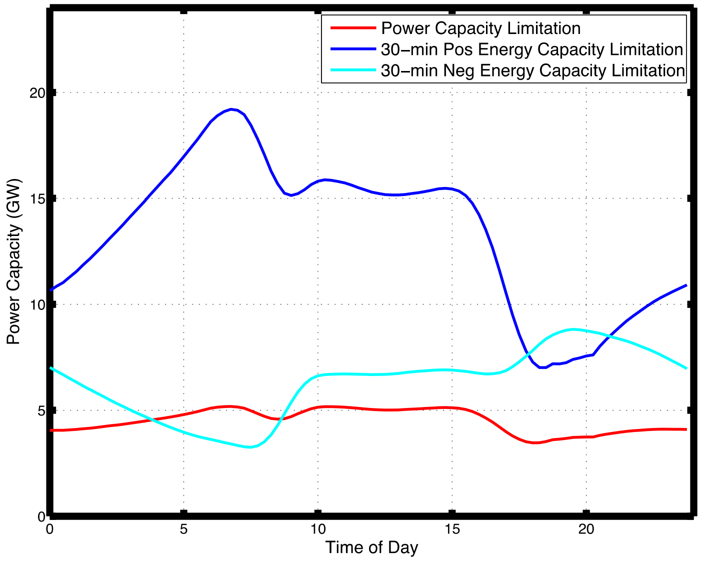

Figure 10: Power and Energy Limitations When Providing Spinning Reserves: Providing spinning reserves requires that there is enough energy to provide power at full capacity for 30 minutes. Thus, EVs face constraints from both grid connection size and energy stored in batteries. Power capacity, shown in red, is a function of the number of connection size, the number of vehicles plugged in (omitting the vehicles currently charging). Positive Energy Spinning Reserves are shown in blue, which represents the power capacity if all the available energy were dissipated in 30 minutes, if the connection size and other physical constraints were not an issue. Power capacity is always more limiting that positive energy capacity. Negative energy capacity limitations, however, are based upon the amount of additional energy batteries can absorb, which becomes the limiting factor early in the morning as batteries become fully charged.

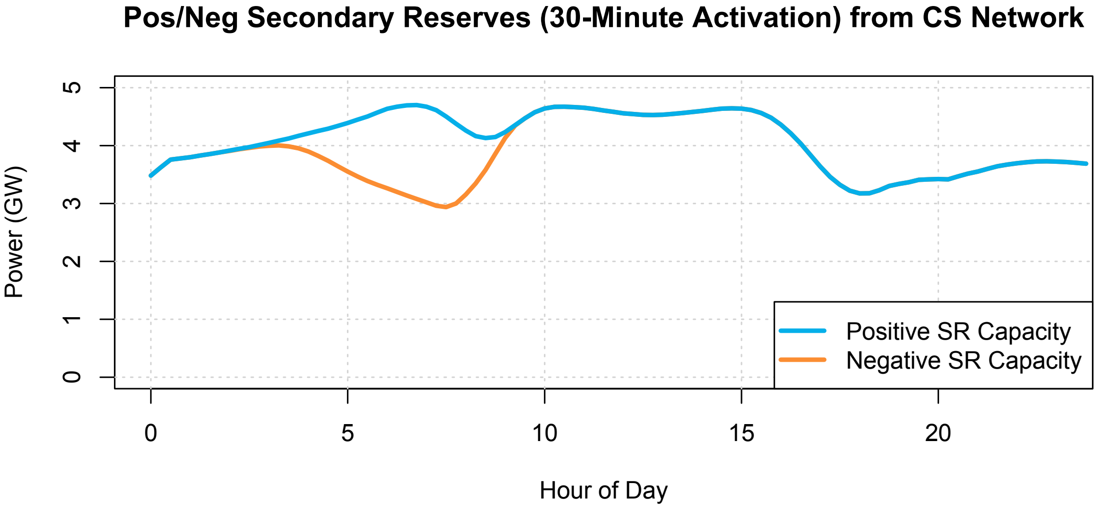

Figure 11: Charge Spot Network Spinning Reserves: Average annual available capacity is shown for spinning reserves based on charge spot utilization only. Negative reserve capacity falls

through the evening as batteries are charged overnight. For all other hours of the day, energy capacity is not a limitation but rather the power capacity of the vehicles plugged in.

3) Tertiary Reserves: Tertiary Reserves require long-term changes in planned load. We calculate Tertiary Reserves as four-hour deviations from an Expected Charge Plan while staying within operating constraints of EV needs. Figure 12 shows the operating limits of the cumulative energy consumption in the CS network.

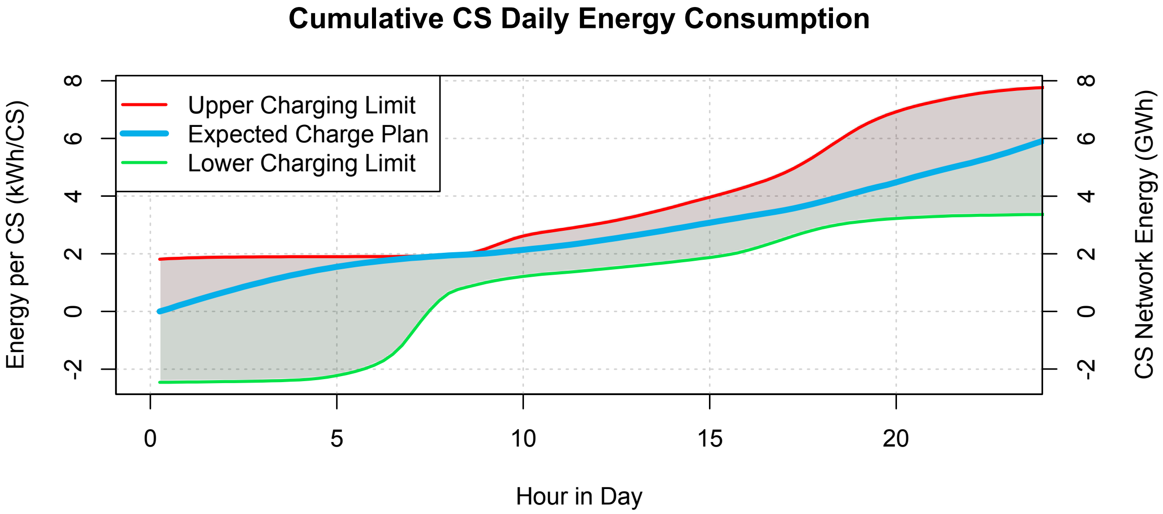

Figure 12: Cumulative Charge Spot Daily Energy Consumption: Energy consumption in the charge spot network with the expected consumption along with lower and upper limits. Upper limit is calculated by charging as quickly as possible, as in the Unmanaged Scenario, while the lower limit incorporates shifting load to the latest time possible before a vehicle departs for a trip. Most vehicles are charged by approximately 8am, which is why the Expected Charge Plan and the Upper Charge Plan appear to overlap.

Consumption can be either increased or decreased from the scheduled load to correct and capitalize on system or trader energy imbalances. The upper limit of Figure 12 is calculated by charging as quickly as possible, as in the Unmanaged Scenario. The lower limit, however, does not have strict bounds, but rather is a function of the operations risk we are willing to take to ensure that vehicles have enough energy. The lower limit set here simply defers all expected charging to immediately before the next trip. That said, vehicles depart with exactly the same amount of energy as in the Expected Charge Plan. Grid impacts were not calculated for this lower operating limit. We could defer charging beyond the green line in Figure 12, since the BSS acts as a safety net. Deferring charging past this lower limit, however, does not indicate that the BSS will necessarily be used.

Movements within this charging window have no impact on drivers and therefore come at a near-zero cost to the CNO. The small costs incurred by the CNO include risk of violating Service License Agreements (SLAs) and from differences in energy prices due to charge plan deviations. Note that both of these costs can be either positive or negative. Charging earlier than anticipated reduces SLA violation risk while deferred charging increases the risk. Likewise, spot market energy costs could be either greater or lesser than day-ahead prices.

From these load forecast curves and operation windows, 4-hour increases or decreases in power consumption are shown in Figure 13. Curtailment here tends to be lower during the day since most charging is planned at night to reduce energy costs. Charge plans here are only optimized on energy price, but could be co-optimized with energy costs and secondary reserve availability to increase tertiary reserves.

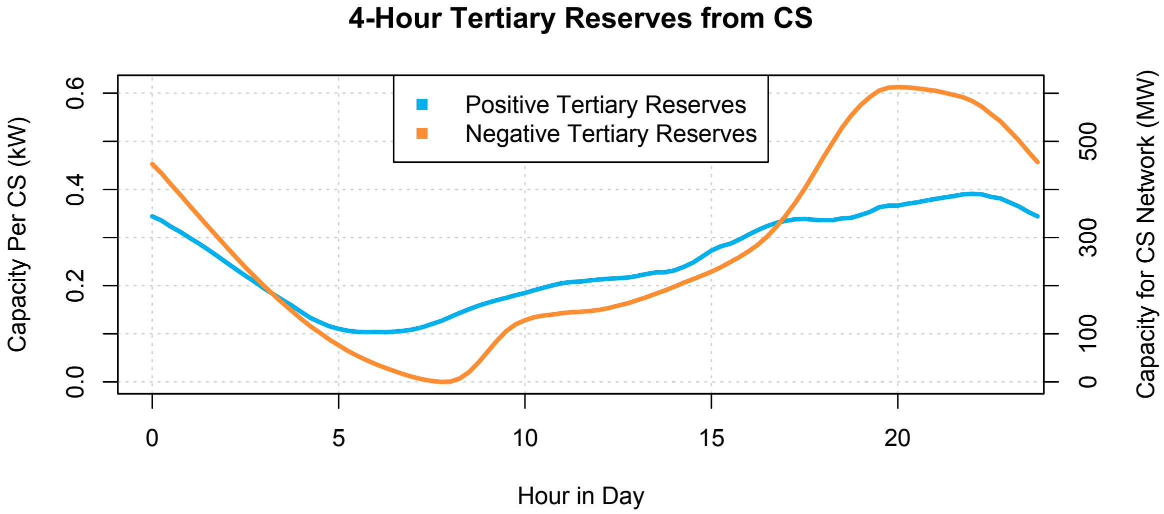

Figure 13: 4-Hour Charge Spot Network Tertiary Reserves: Tertiary reserves are shown for 4-hour load schedule changes performed entirely through load control. Positive tertiary reserves defer charging while negative tertiary reserves accelerate charging. Negative tertiary reserves fall to zero at around 8am as batteries become fully charged.

XI. DISCUSSION

A. The Necessity of the Central Network Operator

Better Place and PJM have shown in this study that managed charging through a CNO using real-time LMPs has the ability to substantially reduce EV grid impacts compared to charging schemes without a CNO. Wholesale energy costs were chosen as the metric for grid impacts because of its physical significance on the power system. Wholesale energy costs, which are calculated using nodal LMPs, include the costs of energy, congestion, and losses, meaning that any cost from generation to delivery to the nearest transmission substation is reflected by LMPs. We therefore believe that any credible charging scheme that aims to reduce grid impacts should aim to reduce increases in wholesale energy costs, LMPs, and the costs to the corresponding price responsive demand (PRD). In order to reduce increases in LMPs across the power system, EV networks must be managed by a CNO to provide the various forecasting, measurement, and control.

The TOU and CNO Scenarios have remarkably different results despite the similarity between the scenarios. The differentiating factor is essentially the CNO with real-time pricing. Although the argument may seem to be that real-time pricing is the key to reducing grid impacts, a CNO is the actually enabling entity that allows for the price predictions and responses to those real-time prices. Responding here refers both to managed charging as well as BSS routing. Both the TOU and CNO Scenarios have predictions for vehicle energy needs, but the CNO is the only entity capable of aggregating the energy needs across the network to make a prediction for system-wide prices. Although there may be other methods where distributed intelligence could be used to make price predictions without measures of aggregate load, it is unlikely that those methods will out-perform the capabilities of a CNO that has the same or more information.

Finally, with both TOU prices and to some extent real-time prices, there is the fear that multiple actors responding synchronously to the same price signal will cause rapid changes in load. Although local mechanisms can attempt to avoid a uniform response through random charging delays, frequency sensing, or an alternative method, only a CNO has the price incentives make sure all actors do not behave identically. We intentionally modeled the TOU Scenario to avoid this synchronous behavior. With such strong price signals from a TOU schedule, however, we still observe relatively rapid changes in load when the price tier switches.

B. Reflection on Scenario Results

The Unmanaged Scenario is relatively simple to understand since charging occurs immediately after vehicles are plugged in. It is important to note here that the Unmanaged Scenario does not represent the upper limit for the impact EVs may have on the power system. For example, we see in Table 1 that the TOU Scenario is actually worse than the Unmanaged Case in two of the weeks we evaluated. The simplest explanation here is that our metric for impact is based on LMPs, therefore a deviation from the charge plan in the Unmanaged Scenario is not necessarily any better or worse off in the TOU Scenario because it is not optimizing on LMPs like the CNO Scenario does.

At first glance, it may seem surprising that the performance gains of the TOU Scenario when compared to the Unmanaged Scenario are so small. First, recall that only 70% of EV charging plans are price sensitive, meaning that 30% charge as they would in the Unmanaged Scenario with no regard for electricity cost. Interestingly though, despite the 70% of customers participating, peak reductions are always less than 70%. The most important factor, however, is that TOU rates do not offer enough incentives to effectively manage charging. For example, if a customer needs energy before a TOU rate will change to another tier, there is no incentive delay charging within that tier. In fact, it is in the best interest of the customer to charge immediately. For this reason, we see mostly similar behavior in the TOU Scenario that we see in the Unmanaged Scenario. Therefore, changes in charging patterns from a TOU pricing schedule primarily occur during hours where plugged in vehicles span two rates. In other words, a TOU pricing schedule is most influential when rates change.

If we extend this logic to the CNO Scenario, where forecasted and real-time rates are different in every time-step, we can infer that continuous price signals are the most important factor in controlling how vehicles charge. To charge in such a way that grid impacts are reduced, those price signals must reflect the real-time LMPs.

C. Policy Implications

This joint study firmly concludes that the increases in wholesale energy cost due to the additional load of 1 million EVs in the Washington-Baltimore Metropolitan Area can be reduced by hundreds of millions of dollars per year if the charging is managed by a CNO responding to real-time LMPs. These savings are without considering the value from various ancillary services and of large-scale dispatchable load for increasing the penetration of renewables, economic dispatch efficiency, and heat-rates for environmental considerations. Existing mechanisms do not necessarily allow CNOs to capture any of this value, which could be used for infrastructure deployment. Based on these conclusions, we emphasize how critically important both the presence of real-time LMPs and of CNOs are to reducing the impacts to the electric power system. Therefore, we recommend that incentives be developed for advancing the power system such that PRD incorporates LMPs and for EV incentives to reach beyond the consumer to CNOs so that intelligent charging networks can be quickly constructed.

XII. CONCLUSIONS

As the first study of its kind, we are aiming to open the door to the analysis and deployment of large-scale distributed and dispatchable loads on power system networks. We have shown the potential value in the energy market and the importance of PRD and managed charging by CNOs. Finally, although this study has only evaluated grid energy cost impacts and, to a lesser degree, ancillary services opportunities, we recognize that dispatchable load can be leveraged for long-term planning, to optimize generator dispatch, defer capital expense upgrades on transmission and distribution infrastructure, and increase the capacity factors and penetration of renewables. We suggest these topics as opportunities for further study.