Cost-Optimal, Robust Charging of Electrically-Fueled Commercial Vehicle Fleets via Machine Learning

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***Abstract*—Electrification for commercial vehicle fleets presents opportunity to cut emissions, reduce fuel costs, and improve operational metrics. However, infrastructure limitations in urban areas often inhibit the ability to charge a significant number of electric vehicles, especially under one roof. This paper highlights a novel controls approach developed at GE Global Research in conjunction with Columbia University to fulfill the stated needs for intelligent charging of a commercial fleet of electric vehicles. This novel approach combines traditional control techniques with machine learning algorithms to adapt to customer behavior over time. The stated controls system is designed to regulate the charging rate of multiple electric vehicle supply equipment devices (EVSEs) to facilitate cost-optimal charging subject to past and predicted building load, vehicle energy requirements, and current conditions. In this embodiment, the system is primarily designed to mitigate electric demand charges that may otherwise occur due to charging at inopportune times. The system will be deployed at a New York City FedEx Express delivery depot in partnership with the local utility, Consolidated Edison Company of New York.**

Keywords—Electric vehicle (EV); smart grid; peak demand; machine learning; artificial intelligence; support vector machine (SVM); support vector regression (SVR); controls; optimization; infrastructure; supervisory control and data acquisition (SCADA)

I. INTRODUCTION

The enactment of the renewable fuel standard in the past decade occurred in the backdrop of a decline in domestic oil production and an increasing demand for transportation fuels [1]. There has been heightened awareness concerning the environmental impacts and associated health implications of burning fossil fuels for transportation needs. In 2011, the United States Environmental Protection Agency (EPA) noted that the transportation sector accounted for nearly 28% of the nation's greenhouse gas emissions [2]. Furthermore, the International Agency for Research on Cancer (IARC), part of the World Health Organization (WHO), classified diesel exhaust as a carcinogen in 2012 [3].

The oil dependence of the transportation sector was labeled among the greatest threats to the energy security of the United States based on research conducted by the Oak Ridge National Laboratory [4]. The use of electricity to fuel transportation requirements can be part of the solution towards these needs and concerns, especially when such electricity is generated from renewable sources. Indeed, governments have stated that such use of renewable energy for transportation fuels would help their given nations reduce their dependence on imported energy from politically volatile regions across the globe, further leading to balanced energy prices and consistent supply that would in turn result in positive ramifications for their respective economies [5].

For a commercial application, the substitution of diesel or gasoline powered vehicles with all-electric replacements can not only reduce emissions, but also offer benefits including lower fuel costs, reduced maintenance, and improved operations due to the ability to refuel in-house. However, as fleet managers examine the potential of replacing their vehicles with electric alternatives, the impact to the local electricity grid should be analyzed, including buildings, campuses and distribution grids. Concentrated electric vehicle (EV) charging at a depot location can impose a significant load on a building's electrical infrastructure and respective supplier distribution grid [6]. In addition, many commercial buildings have demand charges included in their monthly utility bills. Such demand charges are based on the peak average power consumption in kilowatts (kW) for a time interval of 15, 30, or 60 minutes through a billing period [7]. Charging of electric vehicles during a concurrent high building demand could thus significantly penalize the operator with a large increase in their utility bill. Finally, given the absence of a traditional gas or diesel fuel backup, such vehicles must be robustly charged to ensure their ability to fulfill their commercial needs in order to be viable.

A supervisory control and data acquisition system (SCADA) can be put in place to determine when and how quickly each of the electric vehicles would charge, thus reducing the possibility of an increased demand charge that would otherwise adversely impact the effective fuel costs for a fleet of EVs. In time-of-use electricity markets, such a system could potentially use the varying cost of electricity with respect to time to further reduce those effective fuel costs for the fleet, subject to usage requirements. Thus, such a system would not only require knowledge of the particular application to ensure consumption needs would be met, but also the forecasting of future load with specified confidence intervals in order to optimize electricity delivery to the fleet at hand. Given the commercial nature of such an application, the optimized delivery may need to occur without the availability of up-to-

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Fig. 1. FedEx Express Navistar eStar all-electric vehicle (left) plugged into a GE DuraStation™ EVSE (right).

date vehicle-specific information including state-of-charge or where a given EV is plugged in, as a means to reduce the infrastructure investment required for mass adoption of the system.

Such a system was designed, tested, and is scheduled to be deployed at a FedEx Express delivery depot in the City of New York. FedEx Express, a global industry leader providing express shipment delivery for more than 3.9 million shipments every business day [8], has ten Navistar eStar all-electric delivery vehicles with an 80 kilowatt hour (kWh) battery pack (72 kWh useable) at the stated location. The vehicle has an electric top speed of 50 miles per hour (mph) and an advertised range of 100 miles with the given battery capacity [9]. An image of such a vehicle appears in Fig. 1. To support the charging of these vehicles, ten GE DuraStation™ electric vehicle supply equipment (EVSE) devices are installed at the depot, notated in Fig. 1 as well.

The remainder of this paper describes our approach towards these objectives, including overall system architecture, the machine learning approach adopted for load prediction, cost-optimal delivery given problem constraints, system robustness considerations, impact studies, and future direction, followed by concluding remarks.

II. System Architecture

A. System objectives

The system is architected to meet two primary objectives for the motivations outlined thus far:

1) Allow the electric vehicle fleet to be always charged to sufficient levels for commercial activities

2) Accomplish the prior goal in a cost-optimal manner

This ordering is important in that is signifies that operations must not be disrupted in order to achieve a possible cost savings from the utility. In other words, the system should be designed robustly in a manner that is transparent to the commercial user and as devolved of active human-involvement as possible to be of maximum utility in such an environment.

B. Software architecture

The overall software architecture for the high-level data flow for the system appears in Fig. 2.

A machine learning system by Columbia University's Center for Computational Learning Systems predicts both total building load as well as charging load in kilowatts (kW) for the fleet of electric vehicles over the subsequent 24 hours using a support vector regression (SVR) model with carefully selected covariates. Such covariates include historical load, holiday schedules, and ambient temperature and humidity. This allows the system to calculate the predicted building load without any electric vehicle usage – or net building load – by subtraction of the aforementioned elements. In addition, a probability distribution of the number of vehicles plugged in over the subsequent 24 hours is also tabulated and sent onwards to the power profile optimizer.

The power profile optimizer uses this machine learning system's predicted building load in conjunction with the maximum peak over a trailing number of days to provide for optimization of an allowable building peak. This calculation uses discount factors on both of these values to mitigate undesired peaks that would otherwise occur between controls actuations when too close to the allowable peak, to be described in further depth later in this paper. The optimization proceeds to use the probability distribution for when an EVSE usually is charging and the typical energy consumed on a daily basis by each vehicle to ensure that an adequate amount of energy is delivered to plugged-in vehicles over a given period.

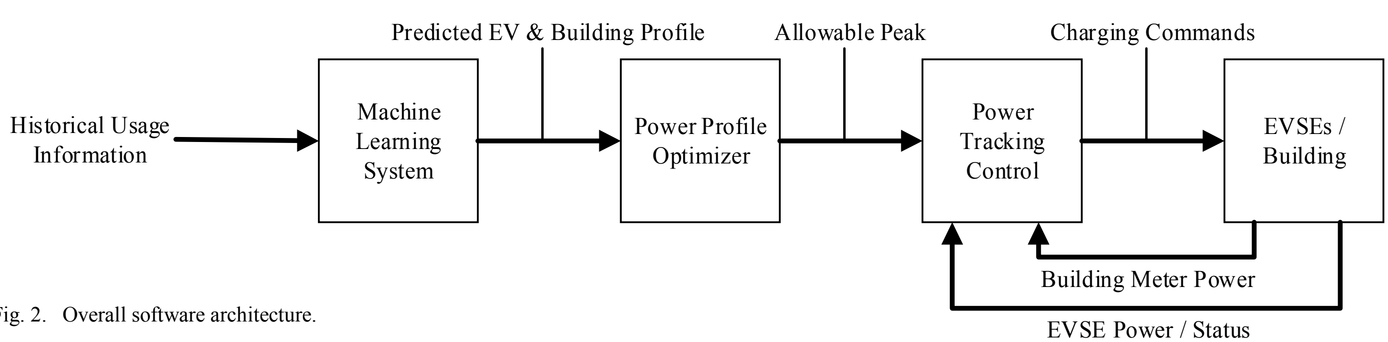

Fig. 2. Overall software architecture.

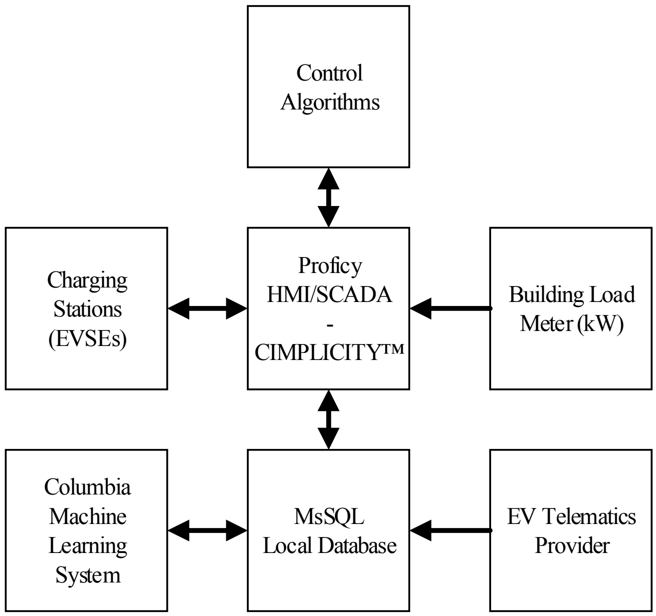

Fig. 3. Hardware and software package architecture.

If not, the optimizer increases this allowable peak as minimally as possible to fulfill this condition, minimizing the demand charges that would occur to the customer while still meeting the needs to perform daily operations.

The allowable peak represents the building load until which electric vehicle charging is permitted by the next component in the system – the power tracking control. After this allowable peak is reached, electric vehicles are still allowed to charge at a user-specified minimum level for robustness. Otherwise, EVSEs which have vehicles ready-to-charge will be throttled between minimum and maximum limits indicated to remain under the allowable building peak, given the current building load measured by the system. These assignments are fairly distributed at the time of execution and are without regards to vehicle state of charge or charging time elapsed. The power tracking control takes into account the building load as well as the state of each EVSE, including measured power consumption, at each control system actuation - as demonstrated in Fig. 2.

It is important to note that since the described control is based on probability distributions and void of knowledge of each fleet vehicle's state of charge, the system would rely on vehicles regularly charging to avoid any vehicles in the fleet running out of fuel. On-board gauges on each vehicle provide an additional mechanism for fleet drivers to avoid running into an abnormally low state of charge. The system furthermore has capability for an operator to designate a given EVSE on manual override to accommodate such urgent situations, at which point the EVSE would charge at an operator-assigned rate regardless of building conditions.

C. Hardware and software package architecture

In Fig. 3, we demonstrate the individual software packages and hardware installations that form the foundation of the system at hand.

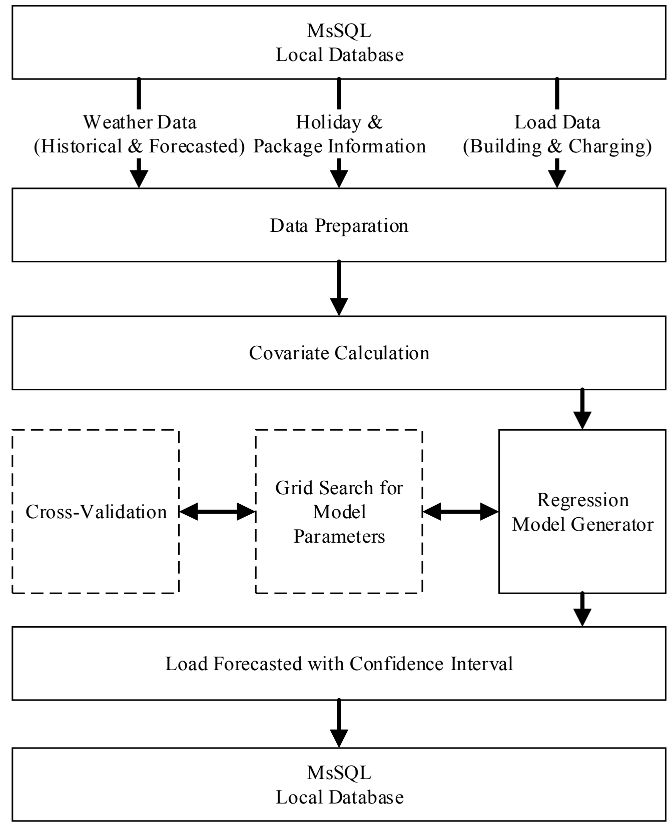

Fig. 4. Columbia Machine Learning System (MLS).

The basis of the system is an industrial automation solution that also serves as the human-machine interface (HMI): Proficy HMI/SCADA – CIMPLICITY™ by GE Intelligent Platforms. This client/server based control solution interfaces with the individual EVSEs and building meter through network connections. All of this meter information is recorded in a local database (Microsoft Structured Query Language Server - MsSQL) interfaced with the CIMPLICITY™ platform. The control algorithms interact with the CIMPLICITY™ platform by obtaining necessary information from the local database and communicating the desired control outputs for each EVSE, after which the signal is propagated to each connected EVSE on the network by CIMPLICITY™ and associated helper packages, namely Object Linking and Embedding (OLE) for Process Control (OPC) servers. The machine learning system outputs its predictions to the local database at a scheduled interval. In addition, vehicle usage and state-of-charge data from a telematics provider for the fleet is downloaded to the database at a prescribed interval. This decoupled architecture via the database allows for robustness considerations to be taken into account when designing the system, as will be discussed further in subsequent sections.

III. Machine Learning System (MLS)

The machine learning system (MLS), demonstrated in Fig. 4, is designed to output the predicted total building load as well as the predicted charging load over the subsequent 24 hours at a regularly scheduled interval. We can follow this process by tracing the appropriate steps of the figure.

TABLE I. BUILDING LOAD PREDICTION COVARIATES & CORRELATION

Covariate	Correlation
Previous week load	0.73
Previous day load	0.68
Previous day average	0.53
Previous week average	0.50
Humidex	0.48
Holiday	0.34
Hour of the day	0.17
Day of the week	0.12

First, pertinent data is collected by the MLS from the MsSQL database. This data includes weather forecasts as well as historical weather obtained via internet data services. In addition, holiday information and estimated package volume information is acquired. This is especially useful in this application as the FedEx depot has multiple sorting facilities with power-intensive conveyor belts and exhaust fans. As such, its power consumption patterns differ from a traditional office building where heating, ventilation, and air conditioning (HVAC) constitute the dominant load. Finally, the historical charging load and building load is procured by the system, after which it proceeds to prepare the data. Such preparation involves accommodating for missing data points and checking data integrity to ensure that they will not adversely bias the model.

Given this filtered data, covariate calculation then commences by the system. It is important to note that the building load and charging load prediction processes occur independently given the differing covariates involved for each prediction. The covariates used for the building load prediction appear in Table I, along with the correlation coefficient of each covariate with the load. To account for HVAC load, a composite of temperature and dew point, humidex, is also incorporated as a covariate. For the charging load prediction, covariates calculated based on the weather were critical, as more heating or cooling led to increased energy consumption by the fleet on very cold or warm days, respectively.

Given these covariates, they are now entered into the support vector regression model. This data-driven technique embeds past-data in multi-dimensional space in order to result in a regression, without knowledge of physical properties outside those specified in the covariates. Once daily, a grid search and cross validation process is performed for the model parameters, as indicated by the dotted lines around the respective boxes in Fig. 4. This tuning process follows the k-folds methodology to ensure the selected model parameters minimize the mean absolute percentage error (MAPE). When prediction is requested at other times, the most recently calculated model parameters are used by the regression model.

The process cumulates with the output of a 24-hour load forecast for both the building load and charging load, with confidence intervals provided for each data point in the prediction. In the event that data integrity or another issue prevents the model from converging properly, a default prediction based on a moving average is provided by the system. This prediction is then stored in the MsSQL local database for use by the system upon the next controls actuation.

IV. COST-OPTIMAL DELIVERY

As mentioned in the architecture overview, the controls solution after the Columbia machine learning system is segregated into two major components – the power profile optimizer and power tracking control. These are now described in detail.

A. Power profile optimizer

The optimizer is responsible for allocating the aggregate energy required to power vehicles controlled by the system over the subsequent 24 hours. This energy required e_{req} is calculated based on estimated daily mileage α for each vehicle i in the fleet and the average amount of energy in kilowatt-hours (kWh) consumed per mile γ for the given vehicles as seen in (1).

$$e_{req}\ [\text{kWh}] = \textstyle\sum_i (\alpha_i\ [\text{miles}] \times \gamma\ [\text{kWh/mile}]) \tag{1}$$

Following this, a probability distribution is obtained with respect to time λ_t regarding when a given EVSE j will have a vehicle available to charge. Thus, for any given time over the upcoming 24 hours, the system can tabulate the estimated number of EVSEs available to deliver power to the fleet E_{EVSE} at time t as seen in (2).

$$E_{EVSE}\ [\text{EVSE}] = \textstyle\sum_j \lambda_t \tag{2}$$

Given this expected EVSE count for any time in the next 24 hours, the algorithm uses the prediction from the MLS. It begins at the troughs of this prediction and calculates the amount of possible delivery of electricity based on the maximum rate of delivery per EVSE, ρ_{max}, for each EVSE available to charge over the optimization interval in minutes. Thus, for any given time, the maximum delivery possible $e_{possible}$ by the system is calculated as shown in (3).

$$e_{possible}\ [\text{kW}] = \rho_{max}\ [\text{kW/EVSE}] \times E_{EVSE}\ [\text{EVSE}] \tag{3}$$

Thus, the system will determine a minimum peak E_{peak} to operate at that fulfills the energy requirements of the fleet, e_{req}, with the prediction provided by the MLS.

Given this minimum peak by the energy allocation procedure, the optimizer proceeds to calculate a power set point, or allowable building load, on which to operate on. This power set point $P_{setpoint}$ is the greatest of:

1.) E_{peak} determined by the energy allocation

2.) Peak billing period building load thus far, minus a discount factor

3.) Predicted peak load by the MLS over next 24 hours, minus a discount factor

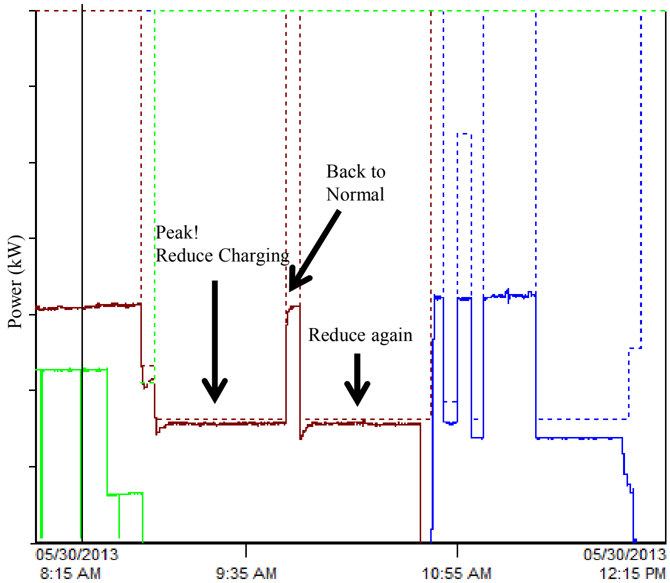

Fig. 5. Power tracking control in operation. Solid lines represent actual charging for a given EVSE while dotted lines represent charging limits, with each color reprsenting a different EVSE on the system.

The reason that the past peak and predicted peak are considered by the calculation is to ensure that any headroom below the peak is not wasted given the objective of only mitigating demand charges for this application. This ensures that the fleet can charge as quickly as possible without incurring a new demand charge. However, given that the controls system actuates every several minutes, uncertainty exists on whether operating too closely to a past peak will result in a new peak should more vehicles plug in between controls actuations. Furthermore, a predicted peak may not actually occur, which could lead to an unnecessary new peak due to charging. For these reasons, both peaks are discounted by optimized factors determined at time of implementation. If the allowable building load is determined by the energy optimization E_{peak}, no discount occurs since that is the minimum peak necessary to meet anticipated customer requirements. It is important to note that the discount factors for the prior and predicted peaks are applied before the choice is made by the optimizer, to ensure that the minimum peak is never violated.

B. Power tracking control

The tracking controller is responsible for allocating power to all the EVSEs in the system, and for remaining below the allowable peak $P_{Setpoint}$ indicated by the power profile optimizer.

The tracking controller uses the real-time building load β_{total} to gauge the current state of operation. Given this real-time building load, total EV charging β_{EVSE} across all EVSEs j at rate ρ is subtracted from this to obtain the current building load power without any EV charging β_{net} as shown in (4) and (5) respectively.

$$\beta_{EVSE}\ [\mathrm{kW}] = \textstyle\sum_j \rho_j\ [\mathrm{kW}] \tag{4}$$

$$\beta_{net}\ [\mathrm{kW}] = \beta_{total}\ [\mathrm{kW}] - \beta_{EVSE}\ [\mathrm{kW}] \tag{5}$$

Given the lack of vehicle-specific knowledge by the system, a manual override is present for the operator to designate a given EVSE to be manually assigned a charge rate. In the event that a given EVSE is in manual mode, it is treated as part of the building and not subtracted out.

Thus, if β_{net} is calculated to be below the allowable building peak $P_{Setpoint}$, plugged-in vehicles that have not completed charging are allowed to charge at between the minimum and maximum rates allowed by the EVSE and/or fleet up to $P_{Setpoint}$. These charging rates are assigned equally among the EVSEs ready to charge. In the event that the net building load without EV charging, β_{net}, does not leave enough or any headroom below the allowable building peak $P_{Setpoint}$, those EVSEs will be set to a minimum charge rate to ensure some charging is occurring to meet any upcoming operational demands of the vehicles.

Fig. 5 demonstrates the power tracking control in operation on multiple EVSEs during testing at GE Global Research, with independent colors representing differing EVSEs under the jurisdiction of the system. When a peak is observed by the controller, EVSE power consumption limits are reduced immediately, as indicated by the dotted lines. As conditions change, these limits are raised appropriately before being brought down again when high load persists. The solid lines representing the power draw of actual vehicles charging can be seen responding immediately to the requests of the EVSE via the control system to reduce their consumption rate.

V. ROBUSTNESS CONSIDERATIONS

In line with the objectives outlined in the system architecture section, the robustness of the system is of critical importance for a commercial deployment. The system must be fault tolerant and resilient to abnormal conditions that may arise in the deployment environment, and resolve any outstanding concerns as independent of human interaction as possible in a fail-safe manner. We now discuss major concerns examined and addressed as part of the design and implementation of the system.

A. EVSE fault tolerance

Each EVSE relies on network communication with the CIMPLICITY™ platform to receive commands on what rate to charge a given vehicle. However, it is quite possible that such communication could be lost or inhibited due to the failure of network hardware, malicious activity on the network, unplugged connections, or a system crash or disablement (e.g. power surge). To mitigate the impact of such events, each EVSE is set at the maximum charge rate when no vehicle is present on the EVSE or when a vehicle has completed charging. When vehicles are actively charging, EVSEs can be throttled to a minimum rate but never suspended, even if above a desired peak, to ensure that energy can always be delivered to the fleet upon system failure.

Furthermore, quirks in network communication packages (e.g. the OPC server) or other strain on the network may cause signal values to be reported in a delayed fashion or erroneously altogether. For this reason, the controls system is designed to check the integrity of each measurement it receives from a given EVSE, including the time of the measurement and whether measurements fall within a user-defined reasonable operating range. In the event such limits are violated, errors are logged and displayed to the user, and the controls system will set such questionable EVSE to a maximum charging rate as a precautionary measure.

B. *Fleet deviation*

As mentioned, the system does not have knowledge regarding which EVs in the fleet are plugged in at any time. As such, it cannot prioritize vehicles that may have higher energy requirements compared to its peers. The system thus relies on regular charging of the fleet's vehicles to ensure this does not cause undesired consequences. The driver is responsible for ensuring vehicles are plugged in regularly and do not fall to critical state of charge levels. A manual override is present for emergency situations to enable a given EVSE to charge at a user-assigned rate, or disable the system in its entirety on a temporary basis.

Furthermore, it is quite possible that the behavior patterns of the fleet will change over time, including deviations from season to season, driver to driver, and as business needs cause routes or the number of vehicles to change. As such, the system has tunable patterns to change the aggregate amount of energy that will be delivered to the fleet to respond to such changes, in addition to feedback from the machine learning system regarding changes in load patterns.

C. *Controls system behavior*

The controls system relies on a variety of software packages and measurements to maintain its operation. Such software packages can be corrupted or require a restart from time to time. The system thus is designed to attempt to self-heal from common failures by restarting appropriate packages and logging such action. In the event such packages or the local database cannot be accessed properly, the system has failovers in place to continue charging the fleet to the best of its ability.

All data being used by the algorithms is checked for integrity in the manner described for EVSEs, including checking the last timestamp and value range of the building load measurement. Should the algorithms fail for any reason, default values to charge at the maximum rate are automatically provided by the system, either for a given EVSE or the entire installation under control as deemed appropriate.

Furthermore, the algorithm has in place limits to guard against undesired feedback from the controls system. For instance, it was observed during testing that changing the charging rate of an EVSE to maximum upon vehicle charge completion would result in certain vehicles noticing such change and start charging again. This would cause the controls system to try to reduce the rate of charging again, resulting in cyclical loop behavior. To mitigate this, an EVSE is set and maintained at the maximum rate upon the first charge completion after a vehicle connection.

D. *Environmental considerations*

Given the all-electric nature of the fleet, the loss of electricity from the grid can cause undesired interruptions in operations. To mitigate this, a diesel generator is present in the facility to provide power to EVSEs in the event of power failure. The servers on which the controls system are based furthermore have an uninterruptable power supply (UPS) to ride through small outages or otherwise shut down gracefully when a longer outage occurs.

Finally, the security of such an installation must be considered. The communications to and from the EVSEs and meters occur on an isolated subnet to mitigate the impact of traffic or malicious activity. Furthermore, the hardware for the controls system itself is located in a locked room and password protected with traditional security packages to guard against SQL injection attacks and viruses.

VI. System Effectiveness

Given the architecture of the system, we now analyze the impact of the designed system for a varying EV fleet size at the location of deployment, simulated for a month in the summer of 2013 based on actual load data recorded by the utility and the demand charge incurred for that month.

This analysis was conducted for three options as follows:

1.) No Control – What peak would be set by all vehicles receiving the maximum charging rate by the EVSE without the presence of any control?

2.) Control Today – What peak would be incurred for the system scheduled to be deployed, with a minimum charging rate always maintained for robustness?

3.) Control Entitlement – What peak demand would be incurred for the system if it did not maintain a minimum charging rate for robustness?

The pricing for the demand charge was used for Service Classification 9, Low Tension Service provided by Consolidated Edison Company of New York. This consisted of a flat charge of \$135.95 per month for the first 5 kW, \$22.34 per kW for up to the next 95 kW, and \$22.07 per kW of demand thereafter [10]. The demand costs stated do not include that of electricity itself, billed on a per kilowatt-hour (kWh) basis.

The plot in Fig. 6 shows the results of this analysis. We observe that without control, a new demand charge could have occurred for as little as 12 EVs plugging in and charging at once during peak consumption periods. Even with the minimum charging level maintained for robustness, a new peak is avoided for up to 56 vehicles. Without the use of this minimum charging rate, a new demand charge could have been avoided until 123 vehicles, after which the system would have deemed it necessary to increase the demand charge to meet vehicle energy needs. It can be observed that after this point, the controls system still has a profound impact on mitigating the demand charge compared to an installation without EVSE control.

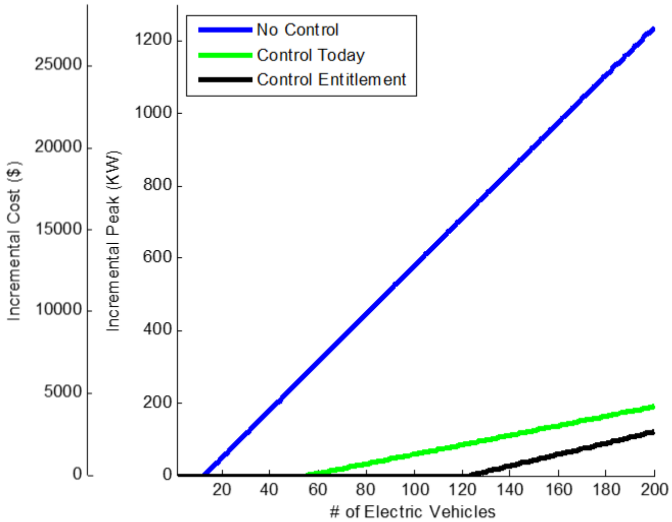

Fig. 6. Incremental demand peak and associated cost incurred for demand based on EV fleet size. Plots are included for the demand without the presence of the controls system, the controls system as will be deployed, and the entitlement of the system without robustness considerations.

From a monetary perspective, with a fleet size of 100 vehicles, the controls system as designed would be able to reduce demand charges by approximately $11,500 per month with respect to an unmanaged fleet, compared to the entitlement savings of approximately $12,500 per month. With a fleet size of 200 vehicles, such demand charge savings expand to about $23,000 on a monthly basis, compared to the entitlement savings of around $24,500 monthly without the presence of a minimum charge rate.

It is important to note that these demand charge savings do not include the cost of electricity delivered or the respective savings achieved from using electricity to fuel the fleet compared to traditional gas or diesel vehicles. Based on usage data from the fleet, it was observed that the cost per mile of the electric fleet was about a third that of diesel operation. Further savings are accrued from the time employees save not needing to refuel vehicles at a diesel station and reduced maintenance.

VII. Conclusion and Future Direction

This paper described a controls system to mitigate demand charges while still meeting the energy requirements of a fleet of electric vehicles in a commercial application. Such a system has the potential to not only reduce effective fuel costs for the fleet, but assist in grid stability via peak management. Results demonstrated that the designed system would be able to achieve a demand charge reduction of up to $11,500 monthly for a fleet size of 100 EVs compared to an unmanaged fleet over the study period examined. Such savings expand to up to $23,000 monthly for a fleet of 200 EVs. These figures do not account for the reduced fuel costs per mile on electricity compared to diesel operation or other operational savings. The system is designed to be fault-tolerant and evolve its prediction of upcoming load over time via a machine learning system. Such optimized delivery was demonstrated without knowledge of EVSE or vehicle specific information such as state of charge in order to reduce the costs and complexities involved in implementing such a system in a commercial environment.

The stated approach can be further accommodated to use real-time vehicle-specific information to prioritize vehicles or optimize for situations where different vehicle types with varying battery capacities may be present in a fleet. The incorporation of time-of-use pricing for cost-optimal delivery would further reduce effective electric fuel costs for such a fleet. Future direction for this technology may also involve using on-site battery energy storage to further reduce demand charges and handle spikes in load, as well as the ability for vehicle-to-grid technology to provide energy from the EVs back to the distribution grid when required for grid stability.

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