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Empirical analysis of electric vehicle fast charging under cold temperatures

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ABSTRACT

This paper presents an empirical analysis of the effects of temperature on Direct Current Fast Charger (DCFC) charging rate and discusses the impact of such effects on wider adoptions of electric vehicles (EVs). The authors conducted statistical analysis on the effects of temperature and constructed an electric vehicle charging model that can show the dynamics of DCFC charging process under different temperatures. The results indicate that DCFC charging rate can deteriorate considerably in cold temperatures. These findings may be used as a reference to identify and assess the regions that may suffer from slow charging. The problems associated with temperature effects on DCFC charging deserve greater attention as electrification of motor vehicles progresses and DCFC usage increases in the future.

1. Introduction

Although the affordability of electric vehicles (EVs) has dramatically improved in the past few years, that affordability is nowhere near that of their gasoline counterparts. EVs at competitive prices with gasoline counterparts are available in the current market; however, they are typically equipped with small battery packs that can only support a very limited driving range per charge. Because high-capacity lithium-ion batteries come with a high price tag, fast public charging has often been considered as an alternative solution to extending the limited driving range of EVs (Schroeder and Traber, 2012; Morrissey et al., 2016; Bernardo et al., 2016; Burnham et al., 2017; Levinson and West, 2017; Neaimeh et al., 2017; Bryden et al., 2018; Yang, 2018). However, fast charging a lithium-ion battery is a complicated process with many shortcomings. One of the most notable limits of charging lithium-ion batteries is the variable charging rate that is susceptible to different environmental conditions—which occurs as the onboard battery management system limits the charging rate to avoid detrimental effects on the battery cells (Motoaki and Shirk, 2017). Cold temperature in particular can considerably degrade the charging rate and extend the duration of charging, which potentially pose challenges in EV operation in cold regions. Therefore, in a large country like the United States where regional climate can vary from coast to coast, fast charger deployment for EVs requires careful consideration regarding the effects of regional temperature on fast battery charging.

However, the literature on EV infrastructure planning and policy in the light of the temperature effects on EV fast charging are limited. Past studies typically assumed the EV charging process with a constant rate of charge (Zhang et al., 2012; Dong et al., 2014; Zenginis et al., 2016; Wang et al., 2017) and the effects of temperature on EV charging were neither accounted for or discussed. However, because cold temperatures have substantial effects on the performance of lithium-ion batteries (Dubarry et al., 2013; INL; Ji et al., 2013; Jaguemont et al., 2016; Lindgren and Lund, 2016), the findings from previous studies on EV infrastructure may alter once the temperature effects are taken into account. However, data acquisition as well as methodologies to estimate the impacts of temperature on EV fast charging are challenging. Ideally, statistical modeling should be applied to data that are collected from repeated experiments in a controlled laboratory environment; however, data collection of such kind is costly in time and budget.

Alternatively, in this paper we propose that fast charging data collected from on-road vehicles can supplement such needs. More specifically, we use on-road data collected from Nissan Leafs that were operated as taxi cabs in New York City for a case study to statistically analyze the magnitude of effects of temperature on EV fast charging. Based on the resulting model, the potential impact of such an effect on wider adoptions of electric vehicles is subsequently discussed. The novelties of this paper are three folds: (1) the application of statistical methods to field data for modeling the electric vehicle charging process; (2) the creation of a charging process model (based on the 2012 Nissan Leaf) that captures the effects of temperature; and (3) the illustration of the effects of temperature on charging efficiency across various regions in the United States. The resultant methodology to construct a charging process model is well suited to be used in the context of the analysis and

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optimization of electric vehicle infrastructure. To the best knowledge of the authors, no study has examined the effects of temperature on EV fast charging based on empirical data.

2. Literature review

It is uncertain how commonly the complexity and shortcomings of the fast charging process are known outside the battery research field. EV manufacturers typically only provide rough approximations of charging duration to the public, without specifying the range of conditions in which that said performance is accurate. For example, the 2012 Nissan Leaf owner's manual states that Direct Current Fast Chargers (DCFCs) are capable of recharging a 2012 Leaf battery from a 10% state of charge (SOC) to an 80% SOC in about 30 min (Nissan, 2012), but it does not state how much time is required to charge from 80% to 100% or how much delay is expected under what conditions. However, the fact is that the rate of charge is variable as it is controlled by the vehicle's onboard battery management system to avoid overcharging and damage to the battery, which can be triggered by a variety of internal and external factors. Among others, cold temperatures have been shown to have particularly high detrimental effects on lithium-ion batteries. A review of the findings on the effects of cold temperatures on lithium-ion battery technology can be found in Jaguemont et al. (2016).

Many EV research areas require a numerical representation of the DCFC charging process. For example, charging station deployment often needs to consider the rate of EV charging because a longer duration of charge means a need for more charging stations for a given demand. However, the problematic effects of temperature on the fast charging and their effects on the level of services of the fast charging have rarely been considered. In fact, the rate of charge is typically assumed constant (Zhang et al., 2012; Dong et al., 2014; Zenginis et al., 2016; Wang et al., 2017). Although this practice provides computational convenience in modeling EV charging, it also introduces positive biases in the performance of EV charging because it does not account for the variable charging rate. Some previous research attempted to incorporate the variable charging rate in modeling. For example, Arias and Bae (2016) adopted a piecewise linear simplification of the charging rate which was originated from Zhang et al. (2012)—it takes 30 min to charge from 0% to 80% capacity and an additional 15 min from 80% to 100%. Arias et al. (2017) also adopted a two-piece charging profile linearization with an assumed duration of 36 min required for full charge. Olivella-Rosell et al. (2015) modeled the charging process as a nonlinear function of SOC and energy required, although the type of charging station considered was 230-volt alternating current charging instead of DCFC. Lindgren and Lund (2016), on the other hand, applied a battery model to simulate charging and discharging of EV batteries in a simulation study of an EV fleet. Although their use of a bottom-up-constructed battery model provides more theoretically sophisticated characterization of EV fast charging, this approach has several shortcomings. Firstly, their battery model was based on a single cell and not a battery pack; thus, to emulate the behavior of the battery pack, the model input and output were multiplied by an assumed number of cells in the pack. This scaling practice would also proportionally scale up the degree of bias and error that the single-cell model contains. The study also placed its focus on level 2 charging (3.6 kW) instead of DCFC, whose process is more difficult to characterize. The charging processes in the above-mentioned studies were based on laboratory observations, and the effects of temperature on fast charging were not examined. Few empirical studies of the temperature effects on EVs can be found in EV literature. Yuksel and Michalek (2015) examined the effects of regional climate variation on EVs in terms of energy consumption, driving and charging patterns, and grid emissions. Specifically, the authors quantified the temperature effects on driving range, energy consumption per mile, and carbon dioxide emissions per mile based on on-road data. Although the authors acknowledged that temperature also affects the charging duration, it was not examined.

To the best of the authors' knowledge, the effects of temperature on EV fast charging rate have never been estimated using on-road data. One obvious reason for the lack of empirical modeling of the effects of temperature on fast charging is the unavailability of the particular type of field data that are needed for the analysis. In order to conduct an empirical study on the effects of temperature on EV fast charging, the field data needs to contain detailed records of variables such as timing, duration, state of charge, temperature, and amount of charge. However, not only are on-road vehicle data rarely collected, but EV charging also has very much to do with environmental conditions and human behavior that are extremely difficult to record or control, which makes many types of analysis simply infeasible. The literature on the use of on-road vehicle data is quite limited. For example, Sun et al. (2015) and Zoepf et al. (2013) both used on-road vehicle data to estimate discrete choice models for the timing of EV charging. Motoaki and Shirk (2017) examined the on-road data collected as part of the EV Project—a large scale project funded by the United States Department of Energy—to investigate the effect of a fixed fee on fast charger utilization. In their study, it was found that DCFCs can be used inefficiently by a driver if the vehicle in question is kept plugged in even after the rate of charge deteriorates considerably. In the data used in the study, each charging event was recorded in terms of time the vehicle was parked at a DCFC charge station (i.e., park duration was not necessarily all spent charging), and the actual duration of time spent solely for the purpose of charging was not known. Therefore, long park duration observed at those stations with nearby amenities could be attributed to the possibility that the driver left his/her car plugged in at the station and went shopping or dining without having to make the trade-off between the time spent at the charging station and the amount of charge. This made it impossible for the authors to tell if the driver intentionally kept the vehicle plugged in at a DCFC even after the rate of charge deteriorated for further charging or he/she simply did not care to come back to the vehicle in time. Moreover, because each charging event record consists of park duration and the amount of charge, the variable nature of the charging rate could not be examined. Temperature at the time of charging was not recorded in the EV Project data; thus, the effect of temperature on DCFC charging was also not examined. The findings from Motoaki and Shirk (2017) show that in an effort to measure the empirical performance of DCFC, some level of experimental control must be placed on both the availability of the charger (i.e., a charger must be available for use when needed) and the behavior of the driver (i.e., timing of charging must be close to optimal) to reduce their effects on the patterns of charging.

3. Data

In an effort to mitigate the problems associated with typical on-road vehicle data discussed above, this present study utilizes on-road data collected from a number of 2012 Nissan Leafs used as taxis as a part of the New York City Taxi and Limousine Commission's Electric Vehicle Pilot Program. During the pilot program several Leafs were provided by Nissan to taxi fleets and owner drivers for use in normal taxi service. Two 50-kW DCFCs were available for use by the Leaf taxis in Manhattan, New York. During the test period, which ran from June 2013 through February 2015, controller area network data were collected by on-board data loggers during vehicle operation and charging. Collected controller area network signals include battery current, battery voltage, SOC, vehicle speed, ambient temperature, charge duration, and vehicle global positioning system location. When the vehicle was plugged in to a charger, it was recorded as a single event for which the battery SOC was recorded both at the time the charging was initiated and the time it was ended—the intermediate process of charging was not included in the data.

Our reasons for the choice of this particular dataset for our study are twofold. First, in taxi operation, the problems of inefficient use of DCFC,

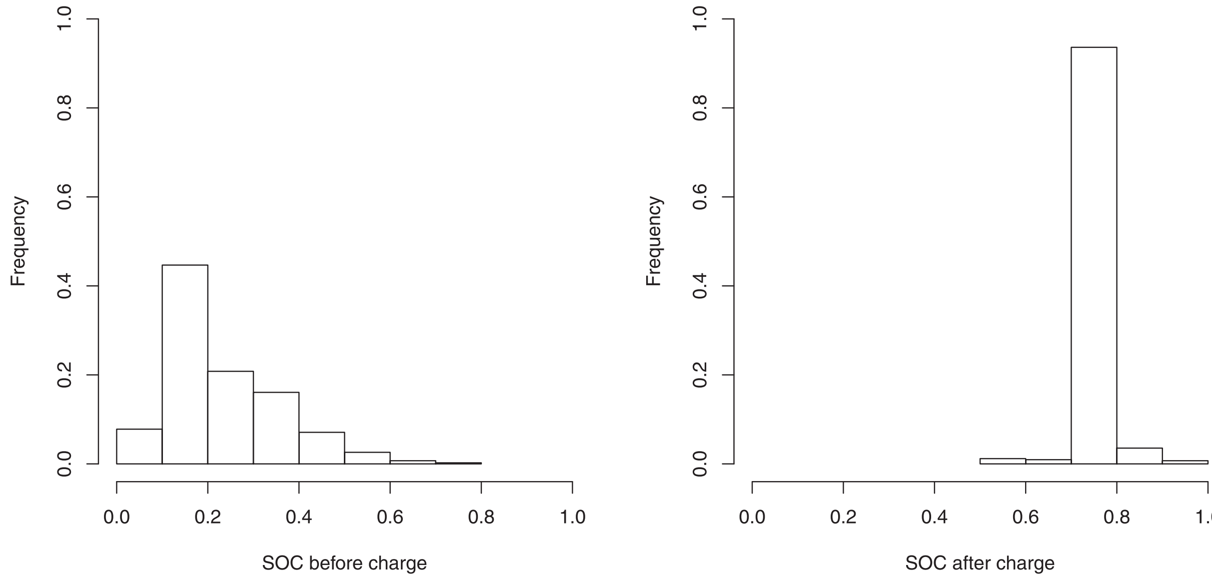

Fig. 1. Histograms of SOC before and after charge.

described in Motoaki and Shirk (2017), are mitigated because for each in-shift charging, the driver needs to make the tradeoff between the time spent at the charger and its opportunity cost (i.e., revenue he or she can potentially earn for that time). Therefore, it was in the driver's best interest to minimize the time spent at a charging station and return to his or her shift as quickly as possible. Because of this, it can be reasonably assumed that the duration of the charge was used solely for the purpose of the charging. Moreover, because the trip to a charging station is a wasteful trip that does not generate revenue, the driver would also attempt to minimize the number of trips to a charger by charging the vehicle to around 80% for each charging event. These hypothesized charging patterns were confirmed by the data shown in Fig. 1, which shows histograms of the SOC at the beginning of charge and the SOC after charge—about 50% of the time, drivers began charging their vehicles when the SOC was below 20% and the battery was charged to about 80% and above more than 90% of the time. Based on this evidence, the utilization of DCFC observed during the pilot program can be said to be near optimally efficient.

The effect of temperature on the charging rate was also confirmed from the data. Fig. 2 shows the plot of the SOC increase and the end SOC against the duration of charging. The color of each observation reflects the ambient temperature at the time of the charging. The figure shows a clear relationship between temperature and charging duration: when temperature is above 25 °C, the relation between SOC increase and the duration seems strongly linear with a steep slope; whereas when temperature is below 25 °C, the relation seems weakly linear with a much flatter slope. Fig. 1 also shows that in cold weather, many of the charging events ended up taking much longer than the expected duration of 30 min. The strong vertical variation in the figure can be attributed to the variation in the initial SOC (SOC at the beginning of charging) as the charging rate becomes low when charging was started at a high SOC. The data contain only the charge events up to the maximum duration of 60 min because the charging stations installed in this study had a safety feature of automatically shutting off the charging after 60 min of a continuous use, in which case the driver had a choice of driving off and resuming his shift or start the second round of charging by resetting the charger, which would be recorded as a separate charging event. Although the reasons are unknown, the data indicated that in some instances the vehicle was unplugged during charging and plugged back immediately after. Because a series of such events were recorded as two or more separate charging events—even though they were likely really one event—the charging events that took place within a 5-min window at the same charger were deemed as errors and removed from our analysis. Similarly, the charging events with duration of less than 3 min were deemed as errors and removed from the analysis.

It is important to acknowledge that only the average charging rate can be computed for each charging event from the data—by dividing the SOC increase by the duration of the charging—because the data on the charging are limited to the initial SOC and the ending SOC without records of intermediate levels of the SOC. Fig. 3 shows two scatter plots of the average rate of charge each plotted against the temperature and the initial SOC. Both plots show approximately linear relationships.

Ambient temperature data for the United States, which will be used to illustrate regional variation in EV fast charging rate, were obtained from the Typical Meteorological Year database from the National Renewable Energy Laboratory. The data consist of hourly temperatures of a typical meteorological year based on records for the year 1976 through 2005 in 925 locations of the lower 48 states.

4. Methodology

As discussed earlier, because the average rate of charge in the recorded charging events has an approximately linear relationship with the temperature and the initial SOC, an ordinary least square regression with the following specification was estimated:

$$\textit{Average rate of charge} = \beta_0 + \beta_1 \textit{Temperature} + \beta_2 \textit{Initial SOC} + \varepsilon. \qquad \text{Model 1}$$

With this specification, the Model 1 estimates the average rate of charge as a linear function of temperature and the initial SOC and fails to account for the continuous deterioration of the rate of charge over the duration of charge. The actual fast charging process is a non-linear process (Motoaki and Shirk, 2017) and a simple multiplication of the average rate of charge by duration can overestimate the amount of charge, especially for a charging event of long duration. Therefore, the current model by itself cannot accurately estimate the continuum of the variable charging rates or the resulting SOC. To fill this gap, the predicted values of SOC from our regression were computed in the following piecewise linear approximation for each discretized minute.

4.1. Piecewise linear approximation

The set of notations used in the derivation are listed in Table 1.

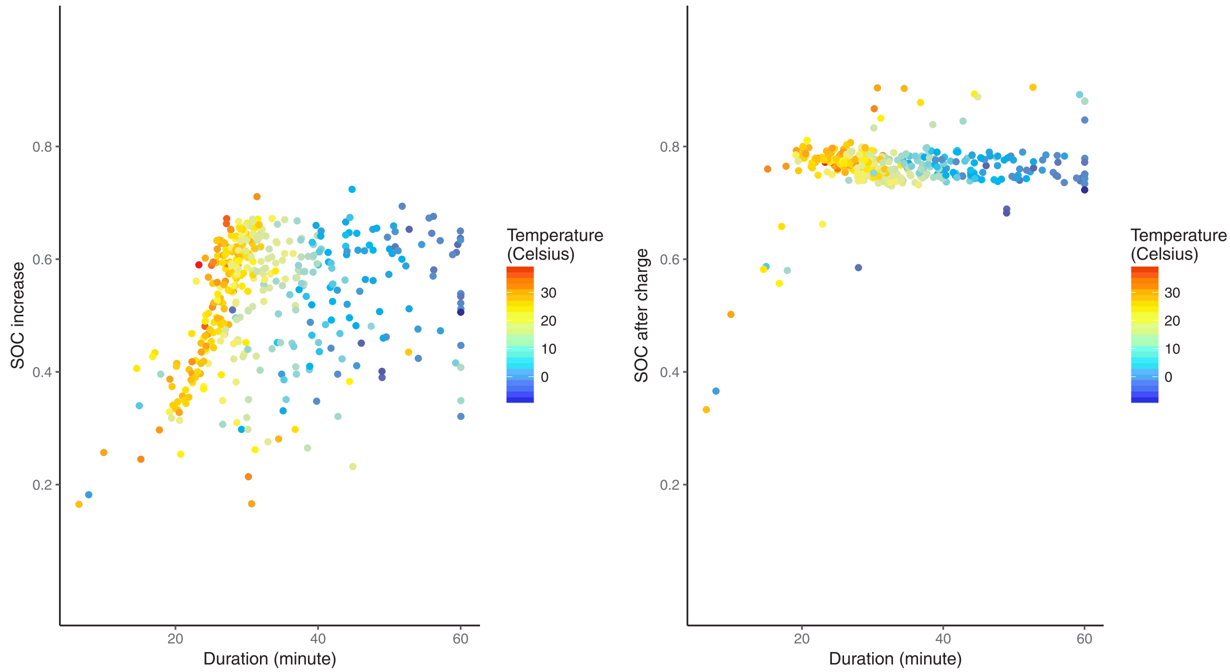

Fig. 2. Relationships of SOC, charge duration, and temperature.

The specification of Model 1 can be written as:

$$S_e - S_o = \beta_0(t_e - t_o) + \beta_1 T(t_e - t_o) + \beta_2 S_o(t_e - t_o) + \varepsilon.$$

Here T is assumed to be constant for a single charging event, because the ambient temperature is unlikely to vary significantly within the charging duration. This also matches the condition in which the experimental data were collected. Let $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$ denote the coefficient estimates and $\hat{S}_e$ denote the predicted value of SOC after charging. Then, for some given values of T, S_o, t_o, t_e, we have:

$$\hat{S}_e - S_o = \hat{\beta}_0(t_e - t_o) + \hat{\beta}_1 T(t_e - t_o) + \hat{\beta}_2 S_o(t_e - t_o).$$

Now consider an arbitrary charging event over the duration of $(0, t)$, and discretize this time range into n intervals of equal length $h = t_{i+1} - t_i$, $i = 0,1,\dots,n-1$. Let $S(t)$ denote SOC as a function of time. Then, the function $S(t)$ can be approximated by a piecewise linear

Table 1
Notations and units used.

S – state of charge in fraction
T – temperature (Celsius)
t – time (minute)
S_0 – initial SOC in fraction
S_e – ending SOC in fraction
t_0 – starting point in time of charging
t_e – ending point in time of charging

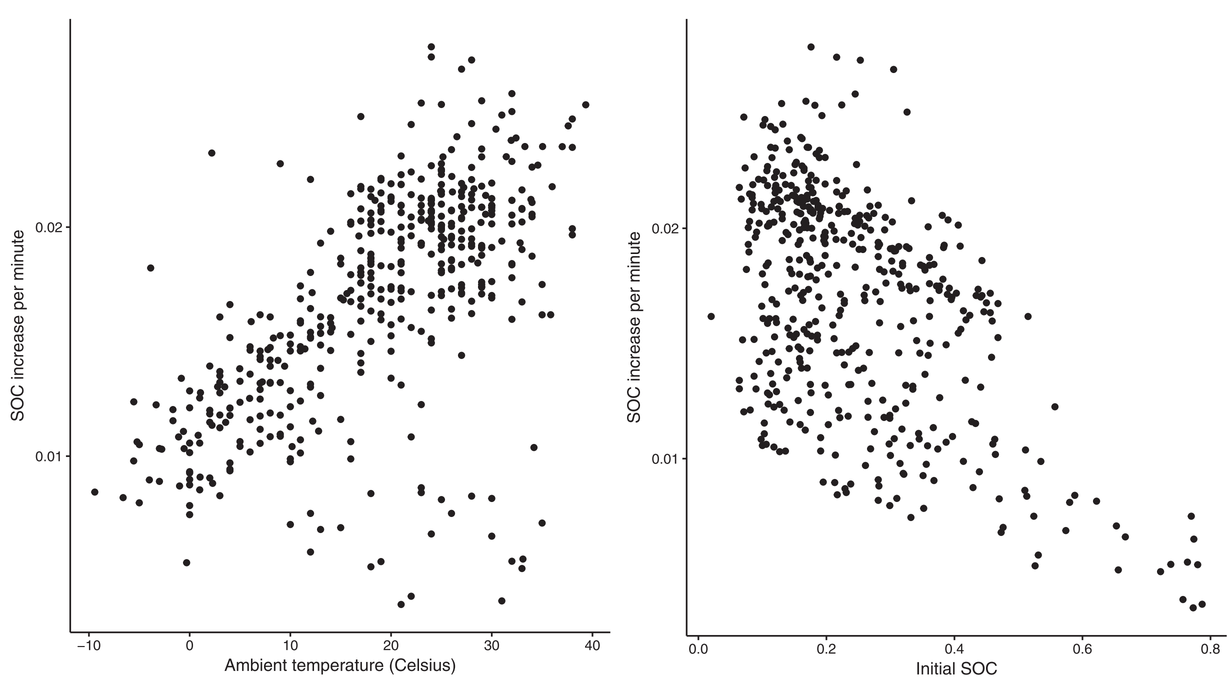

Fig. 3. Scatter plots of SOC increase per minute versus temperature and initial SOC respectively.

function $\hat{S}(t)$ over each interval as:

$$\hat{S}(t) - \hat{S}_i = \hat{\beta}_0(t - t_i) + \hat{\beta}_1 T(t - t_i) + \hat{\beta}_2 \hat{S}_i(t - t_i), \text{ for } t_i < t \leq t_{i+1},$$
$$\hat{S}_i = \hat{S}(t_i), \quad i = 0, 1, \ldots, n-1. \qquad \text{Model 2}$$

Model 2 can be used to approximately predict SOC as a function of time with different initial SOC values and under different temperatures. It is important to note that from Model 2, a smooth (i.e., continuously differentiable) function can be derived by taking the limit as $h \to 0$.

Re-arranging Model 2 and plugging in $t_{i+1} = t,\ t_i = t - h,\ \hat{S}_i = \hat{S}(t_i) = \hat{S}(t - h)$ gives:

$$\frac{\hat{S}(t) - \hat{S}(t-h)}{h} = \hat{\beta}_0 + \hat{\beta}_1 T + \hat{\beta}_2 \hat{S}(t-h).$$

Because $\lim_{h\to 0}\frac{\hat{S}(t)-\hat{S}(t-h)}{h} = \frac{d\hat{S}(t)}{dt}$ and $\lim_{h\to 0}\hat{S}(t-h) = \hat{S}(t)$, if $\hat{S}(t)$ is continuously differentiable, taking the limit of both sides as $h \to 0$ gives:

$$\frac{d\hat{S}(t)}{dt} = \hat{\beta}_2 \hat{S}(t) + \hat{\beta}_0 + \hat{\beta}_1 T.$$

Solving the equation for $\hat{S}(t)$ with the initial value $\hat{S}(0) = S_o$ gives:

$$\hat{S}(t) = \left(S_0 + \frac{\hat{\beta}_0 + \hat{\beta}_1 T}{\hat{\beta}_2}\right)e^{\hat{\beta}_2 t} - \frac{\hat{\beta}_0 + \hat{\beta}_1 T}{\hat{\beta}_2}. \qquad \text{Model 3}$$

Model 3 is a smooth approximation function that also predicts SOC over time with different initial SOC values and under different temperatures. It is important to note the applicable of the ambient temperature T and initial SOC S_0. On one hand, $\lim_{t\to+\infty}\hat{S}(t) = -\frac{\hat{\beta}_0+\hat{\beta}_1 T}{\hat{\beta}_2}$ implies the theoretical bounds $S_0 < -\frac{\hat{\beta}_0+\hat{\beta}_1 T}{\hat{\beta}_2} < 1$; on the other hand, what's more relevant to using Model 3 for predicting charging profiles are the practical bounds that are subject to the support of the data, which will be discussed in Section 6.

5. Result

The regression model had an excellent fit to the data with both R^2 and the adjusted R^2 at 85%. Table 2 shows the coefficient estimates and their 95% confidence intervals. All coefficients were statistically significant at the 1% level. The residuals versus the fitted plot and Q-Q plot of Model 1 showed very weak evidence for misspecification and some violation of residual normality at the tails. For a visual illustration purpose, the predicted values were computed using Model 3 and plotted to show SOC over a 60-min charge duration for 25 °C and 0 °C (Fig. 4). The ambient temperature was assumed to be constant during the charge event. Our model predicts that with 95% confidence, the expected amount of the decrease in the end SOC after a 30-min charge between when the temperature is 25 °C and when it is 0 °C is between 22% and 36% (Table 1).

6. Discussion

This analysis showed that the average deterioration of a 30-min DCFC charge from warm temperature (25 °C) to cold temperature (0 °C) can be as large as a 36% decrease in the end SOC. This indicates that the performance of DCFC can largely vary across the United States due to the variation in regional climate. To illustrate this problem, the SOC values rendered for the locations included in the Typical Meteorological Year database were calculated using Model 3. The coefficients $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$ are given in Table 2, $S_0 = 20\%$ and T_l is the median of the daily maximum hourly temperatures over a year at location l (i.e., T_l is the median of $\{T_{ld}^{\max} | T_{ld}^{\max} = \max_{h=1,\ldots,24}\{T_{ldh}\}, d = 1, \ldots, 365\}$). These values of T_l are chosen to illustrate possible limitations on the prevailing 50-kW DCFC due to impeded charging in cold weather. Charging efficiency is expected to be better than the rendered values in Fig. 5 on half of the days in a year and worse on the other half. The median-temperature day SOC after a 30-min charge, with an initial SOC of 20%, ranges from 49% to 74% over all different regions of the lower 48 states. In general, charging efficiency decreases as one goes further north and increases as one goes further south. As shown in Fig. 5, noticeable pockets of areas with the poorest EV charging efficiencies are found in the Pacific Northwest, the Midwest, north of the Great Lakes region, and the upper Northeast, while the highest EV charging efficiencies are found near the southern state boundaries of California, Arizona, Texas, and Florida.

The degradation of the rate of DCFC charge due to cold temperatures can potentially pose many challenges. For example, delays in fast charging may cause difficulties in maintaining EV operations that need to follow specific schedules. A slower DCFC charging rate can also be a deterrent for consumers living in cold regions to purchase EVs, in addition to other temperature-related issues such as performance loss and degradation of the batteries (Jaguemont et al., 2016) and driving-range loss from cabin climate control load (Yuksel and Michalek, 2015, Zhang et al., 2018).

Future EVs likely have larger battery capacities and require less frequent fast public charging; however, public fast charging will still likely be required for a long-range drive and heavy-duty vehicles, which consume a large amount of energy per mile. Future charging stations will likely be able to charge EVs faster and may mitigate temperature effects; however, the level of potential improvement is unknown—at least in the short run. The present analysis also suggests that the impacts of DCFC charging on the electric grid may considerably vary over seasons in the future once the electricity demand from DCFCs constitutes a significant portion of the total electricity demand. Because the rate of charge can potentially be much higher in warm conditions, DCFC usage may require higher levels of electricity supply in warmer weather, thus impacting the grid more severely. In some regions of the United States, temperatures can fluctuate drastically from day to day or even hour to hour. An extreme level of short-term fluctuation in temperature may make it difficult for an electricity supplier to plan for a sustainable energy supply, especially when the area hosts a large number of DCFCs. Past studies in modeling load demand due to EV battery charging did not account for seasonal variation in load demand due to variable DCFC charging rate (Qian et al., 2011; Zhang et al., 2012; Liu, 2012; Arias and Bae, 2016). To the authors' knowledge, the efficiency loss in EV system performance due to prolonged charging duration in cold temperature or its effects on the electric grid has not been examined. Further research will be needed to address these issues and new policy should consider a variable load demand from EV

Table 2
Coefficients estimate of Model 1.

	Estimate	Standard error	t stats	P value	CI 2.5%	CI 97.5%
Intercept (β_0)	0.015	0.00023	69.00	< 0.01	0.015	0.016
Temperature (β_1)	0.00034	0.0000084	40.54	< 0.01	0.00032	0.00036
Initial SOC (β_2)	− 0.022	0.00072	− 30.33	< 0.01	− 0.023	− 0.020

R-squared: 0.85.
Adjusted R-squared: 0.85.
Degrees of Freedom: 420.

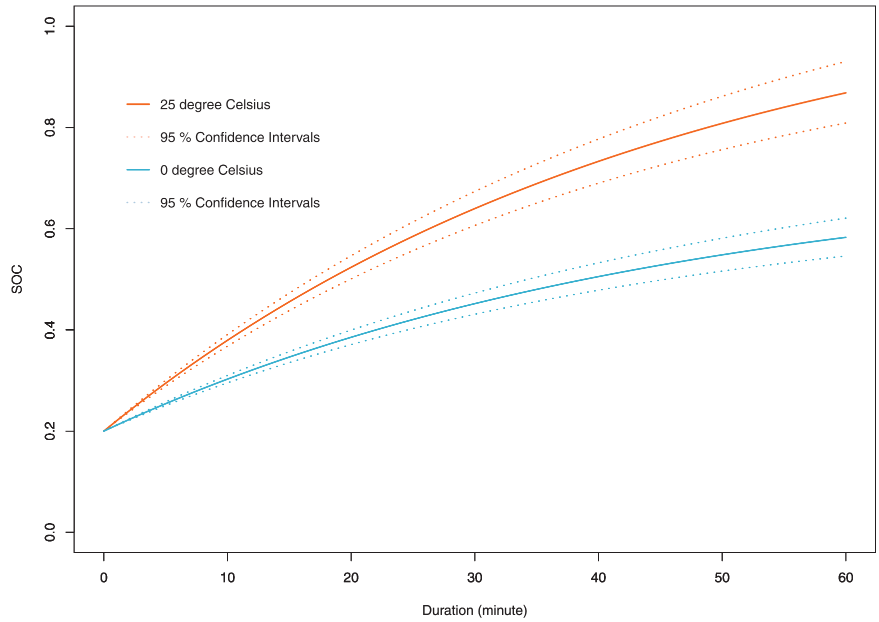

Fig. 4. Plot of predicted SOC profile over time using the smooth approximation function.

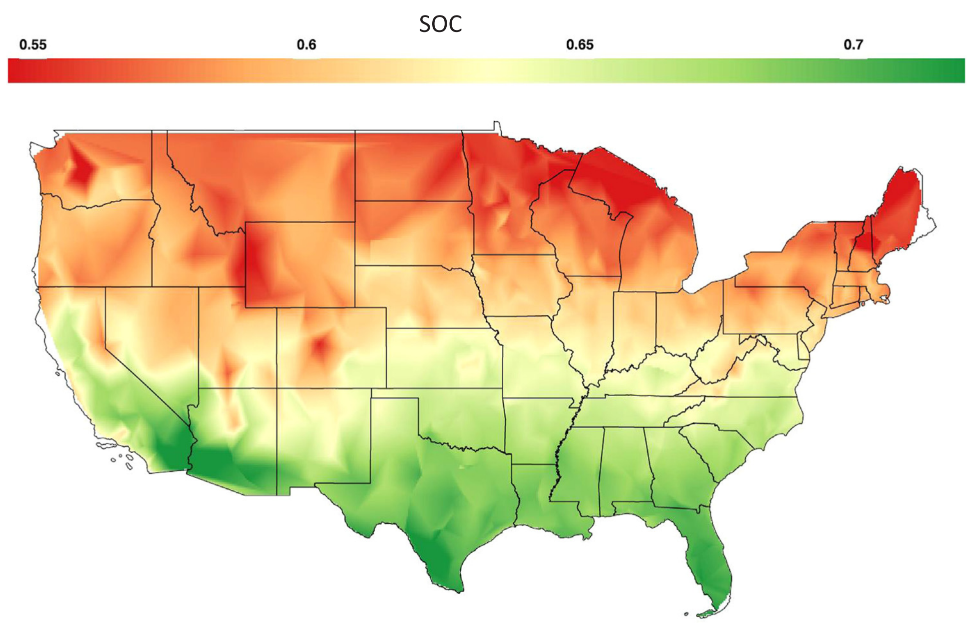

Fig. 5. Predicted SOC after 30-min charge on median temperature day (S_0 = 20%).

charging caused by temperature changes.

It is important to highlight that the present study has limitations needing to be addressed. First, the charging data were collected from one particular model of EV (i.e., the 2012 Nissan Leaf); as such this is just a case study with the Nissan Leaf. Other models of EVs have different battery management systems, energy consumption, and battery capacities; thus, the magnitude of temperature effects on their charging rate, as well as the expected charging duration, likely differs from that reported here. Second, because the on-road data were collected over a period of two years, it is reasonable to expect the vehicles' battery capacity was degraded by several percentage points, especially toward the end of the data collection period. Because the unit of measure used for charging was based on SOC, battery degradation was not accounted for in this analysis. In addition, some measurement errors in SOC are likely present in the on-road data due to the limited accuracy of the battery management system to estimate SOC. In fact, when charging duration was less than five minutes, some of the recorded SOC and kWh charged were inconsistent with each other. We treated those observations as errors and removed them from the data.

The support of our data also has limitations. Our data consist of fast charging with duration of between 1 and 60 min. As shown in Fig. 1, many charging events under severe cold temperatures took 60 min. Charging events with duration of more than 60 min were not recorded in the data because the DCFC installed in the Electric Vehicle Pilot Program shut off after 60 min of use. We did not consider SOC after the charge beyond 60 min because we believed that charging that takes more than 60 min with Nissan Leaf battery is not practically fast charging. The support for the temperature data during charging is also limited to the range of temperatures recorded in Manhattan between 2013 and 2015, where the lowest temperature recorded was − 9.42 °C and the highest was 39.34 °C. Therefore, the approximation function, Model 3, should not be used to estimate changing profile for events under conditions that are beyond these the support of the data, which should be limited to durations between 1 and 60 min and temperatures between − 9.34 and 39.34 °C. Finally, due to the availability of data, ambient temperature was used as a proxy for battery temperature which is what actually affects the charging rate.

7. Conclusion

The Nissan Leaf taxi data showed that the operation of the EV taxies suffered from considerable deterioration in the charging efficiency in cold temperatures. By applying a piecewise linear approximation with a regression, this study statistically estimated the effects of temperature on the average fast charging rate and constructed a charging model that can show the dynamics of the DCFC charging process under different temperatures. These results identified both the particular type of data needed to examine the performance of DCFC charging and an accompanying methodology to analyze such data. Using the charging model, we showed that the DCFC charging in some of the regions in the United States suffer from considerable deterioration in the charging efficiency in cold seasons. Our analysis may be used as a reference to identify and assess the regions that may suffer from severe charging inefficiency.

The problems associated with temperature effects on DCFC charging deserve great attention as electrification of motor vehicles progresses and DCFC usage increases in the future. Because the temperature effects were neglected in the past research on EV infrastructure planning, these results may alter the previous findings. In particular, these findings pose additional uncertainty in the practicality of EV (with the current battery technology) in some of the regions in the United States in the light of their climatic characteristics. Future research in the fast charger location planning as well as EV operations that involve fast chargers, must consider climate variability.

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Notes

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