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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,