Sustainability, Resiliency, and Grid Stability of the Coupled Electricity and Transportation Infrastructures: Case for an Integrated Analysis

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Abstract: Electrified vehicles (EVs) couple transportation and electrical infrastructures, impacting vehicle sustainability, transportation resiliency, and electrical grid stability. These impacts occur across timescales; grid stability at the millisecond scale, resiliency at the daily scale, and sustainability over years and decades. Integrated models of these systems must share data to explore timescale dependencies, and reveal unanticipated outcomes. This paper examines EV adoption for sustainability, resiliency, and stability effects. Sustainability findings, consistent with previous studies, indicate that electrification generally reduces lifecycle greenhouse gas (GHG) emissions, and increases SO_x and NO_x. Electrified vehicles enhance vehicle resiliency (ability of vehicle to complete typical trips during fuel outage). Coupled results enhance EV resilience research, finding that a 16-km (10-mi) all-electric range plug-in hybrid EV improves resiliency ~50% versus a gasoline-only vehicle. Increasing EV market share reduces grid stability. Stability depends upon charging profiles and background electrical demand. Stability-related grid outages increase with EV market penetration. This paper modeled these systems in their coupled form across timescales yielding results not obvious if the systems were modeled in isolation. **DOI:** 10.1061/(ASCE)IS.1943-555X.0000251.

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Introduction

The potential benefits of electrified vehicles (EVs) have been subject to much research across multiple time scales. Electrified vehicles include hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs), which can charge using grid electricity or use gasoline, and battery electric vehicles (BEV), which exclusively use grid electricity. In the long timescale, some researchers claimed that EVs can improve the sustainability of personal transportation by displacing gasoline use with nonfossil-based electricity, thereby reducing greenhouse gas (GHG) emissions and other airborne pollutants [Elgowainy et al. 2010; Electric Power Research Institute (EPRI) 2007; Kintner-Meyer et al. 2007; Li et al. 2013; MacPherson et al. 2012; Saber and Venayagamoorthy 2011; Samaras and Meisterling 2008; Sioshansi et al. 2010]. Others argued, however, that the lifecycle GHG emissions of an EV are not necessarily less than that of a conventional vehicle (CV) with only an internal combustion engine. This is because the emissions associated with manufacturing and operating the CV can be less than those for an EV, if the EV's electricity comes from GHG-intensive regions [(i.e., grids dominated by coal fired power plants); Hawkins et al. 2013; MacPherson et al. 2012; Samaras and Meisterling 2008].

Similarly, in the short timescale, EVs could facilitate enhanced resilience of transportation to disruptive events such as widespread, long-term gasoline shortage due to fuel crises as exemplified in the 1970s in the United States (Peskin et al. 1975; Rudel 1982), or more recently due to extreme weather events such as Hurricanes Katrina and Irene, and Tropical Storm Sandy (Abramson and Redlener 2013). However, added EV charging load could disrupt the electric grid, with the potential for demand to exceed generation, or for problems with grid stability.

Such questions are hard to answer because the problem of studying the full impact of EVs spans two infrastructures [(1) electricity, and (2) transportation] and multiple timescales. As such, an

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accurate answer, especially for their sustainability, resiliency, and stability impacts, requires an analysis framework covering both infrastructures at these multiple timescales. Much work in EV sustainability examines pollutant emissions, energy consumption, and resource depletion effects at the long timescale (Elgowainy et al. 2010; EPRI 2007; Hawkins et al. 2013; Samaras and Meisterling 2008; Sioshansi et al. 2010). Research focused on the electrical grid impacts of EVs, and the transportation resilience of EVs focus on shorter timescales (Clement-Nyns et al. 2010; Hadley and Tsvetkova 2009; Kintner-Meyer et al. 2007; Kundu and Hiskens 2014; Marshall et al. 2015). Hence, there is a lack of integrated analysis in the literature.

The research reported in this paper describes and systematically applies a set of tools to evaluate the coupled system sustainability and resilience of electrified vehicles, focusing on long-term environmental sustainability metrics (vehicle and electricity pollutant emissions) along with short-term resiliency metrics (capacity to complete trips in case of a fuel shortage) and electrical system stability metrics (unintended electrical distribution network failures). The research reported in this paper simulates two charging scenarios of five vehicle designs, at 14 vehicle penetration levels to determine vehicle use phase GHG, NO_x, and SO_x emissions. These emissions are incorporated in a full vehicle lifecycle assessment (LCA). The charging scenarios are cosimulated with three different trip-scheduling algorithms given 10 gasoline supply disruption scenarios to determine resilience. The charging scenarios are simulated within an IEEE-34 distribution feeder (IEEE 34-node test feeder model) to capture short timescale disruptions.

Background

Sustainability

Vehicles utilize fossil fuels for motive power, and personal vehicles account for 83% of all trips in the United States (Santos et al. 2011). Transportation accounts for 28% of total U.S. energy use and 34% of total CO_2 emissions in 2013 (USEIA 2014a). The research reported in this paper measures sustainability performance by evaluating greenhouse gas emissions (including CO_2, CH_4, and N_2O) and criteria air pollutants (SO_x and NO_x). Greenhouse gases have global implications, whereas criteria air pollutants have a greater impact on air quality and human health at the local and regional scale. The environmental impacts of plug-in vehicle technology are determined largely by the portfolio of electricity generation assets used to charge the vehicle (Elgowainy et al. 2010; EPRI 2007; Samaras and Meisterling 2008), the size and chemistry of the vehicle's battery (Hawkins et al. 2012; Sullivan and Gaines 2012), charging patterns (Kelly et al. 2012; Weiller 2011), and vehicle usage including driving behavior and trip selection. To realize the potential environmental benefits of plug-in technology it is important to understand the relationships among these variables.

Improving vehicle sustainability through both technology and policy methods have been examined in previous studies. From a technology perspective, PHEVs often have good fuel economy and low tailpipe emissions due to the transmission hybridization (Bandivadekar et al. 2008; Baptista et al. 2010; EPRI 2007; Kintner-Meyer et al. 2007; Lane 2006; Samaras and Meisterling 2008; Sioshansi et al. 2010), but a reduction in GHGs is not guaranteed. While most U.S. electrical grids provide electricity with fewer GHG emissions than gasoline (MacPherson et al. 2012), EVs could have higher GHG emissions than gasoline if electricity from the grid is produced by coal plants (Saber and Venayagamoorthy 2011).

Resiliency

The lack of diversity in transportation energy sources (gasoline) and the reliance on a single mode of transportation (passenger car) can cause the transportation system to degrade (lost travel) when a disruption occurs. The ability to maintain desired levels of a system's performance during a disruption increases with system resilience (Vugrin et al. 2010), which is primarily achieved by system adaptation as resources are exchanged among system elements (Jackson 2010). Electrified vehicles enable adaptability by allowing an electric power system to share energy resources with the transportation system during disruptive events, thus improving resilience.

The definition of resilience is neither precise nor consistent across differing contexts or disciplines. Bhamra et al. (2011) identify 15 distinct definitions of resilience, yet find that the concept of a resilient system is closely related with the capability of an entity to recover a stable state after a disruption. Differences in the definition of resilience across disciplines are often based on whether resilience is concerned with deviations from a steady state, termed engineering resilience, or with changes between entirely different states, termed ecological resilience (Holling 1996). With engineering resilience, resistance to disturbance and speed of recovery are key measures. The magnitude of disturbance a system can adapt to and still function is a key measure of ecological resilience (Holling 1973).

Fundamental to metrics of system resiliency is the system's performance under disruptive conditions. Resilience metrics measure the system's ability to either reduce the impact of change, adapt to it, or recover from it (Vugrin et al. 2010). Electrified vehicles create interdependencies between the electric power and transportation systems that may impact system resilience in one or both systems (Ibáñez et al. 2010). If vehicle electrification provides additional modes of travel or energy sources such that the system is more able to absorb or adapt to a disruption without complete loss of performance or structure, it has improved system resilience (Jackson 2010).

System resilience is also influenced by behavioral responses unique to disasters (Jackson 2010; Rose 2009). Surveys from the 1970s oil crises in the United States indicate that during actual or perceived fuel scarcity, households respond by eliminating or reorganizing discretionary or noncritical trips (Peskin et al. 1975; Rudel 1982). This behavior has a positive effect on system resilience as measured by a household's ability to complete all critical trips. Yet, surveys from historical oil shocks suggest that households do not make a significant short-term switch in travel mode due to gasoline price increases, or shortages (Diltz 1982; Noland et al. 2002; Peskin et al. 1975). This lack of behavioral adaptivity negatively effects system resilience by impeding recovery of a supply-constrained transportation system.

Grid Stability

Market research reports suggest that by 2020 EVs may account for 20% of automobile sales in the United States (Book et al. 2009; Lache et al. 2008), but government predictions are much more modest, suggesting annual sales below 2% between now and 2025 (USEIA 2014b). In many cases, these vehicles will charge from residential distribution feeders. Financial incentives will likely encourage charging overnight, when background non-EV demand is low, thus EV load will contribute a significant portion to total demand on residential feeders (SAE 2010). Residential real-time pricing structures are now available in several electricity markets (DTE Energy 2014; Plug in Illinois 2014; Southern California Edison 2014), thus encouraging off-peak charging. Without managing this additional load, there is the potential to increase peak demand, thereby straining the electrical system.

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When electricity demand is composed of large numbers of similar devices, relatively benign events can synchronize their response, resulting in potentially destabilizing collective behavior. Such a situation arises with fault-induced delayed voltage recovery [(FIDVR); NERC 2008], where a voltage sag leads to large numbers of residential air-conditioner compressors stalling (Kosterev et al. 2008). The high current drawn by the stalled induction motors depresses voltages further, and cascading voltage collapse may result. Voltage sag is a reduction in voltage below a specified amount (e.g., 10%) of nominal.

The response of EV chargers to power quality events is governed by SAE J2894 (SAE 2011), which updates a previous report (EPRI 1997). As with FIDVR, the response of EV chargers to low voltage events is of particular interest. Two cases are covered in SAE J2894 (SAE 2011), as follows: (1) voltage sag, in which EV chargers must remain energized while voltage supply drops to 80% of nominal for up to 2 s; and (2) momentary outage, in which EV chargers must ride through a complete loss of voltage for up to 12 cycles. Situations where voltages sag below 80%, but remain nonzero, are not explicitly covered by SAE J2894 (SAE 2011). Voltage sag is only one possible indicator of electrical grid stability.

Voltage sags often affect entire distribution feeders, and may be more widespread when initiated by a transmission system event. Distribution networks will likely experience voltage sags sufficient to cause large numbers of EV chargers to trip. After such trips, SAE J2894 (SAE 2011) recommends that restarting be delayed to minimize additional grid problems (Ihara and Schweppe 1981). Upon recovery from the voltage sag, the feeder would experience much lighter load, and consequently voltages would exceed their predisturbance values. Shunt capacitors, which are common on distribution feeders, would further contribute to this voltage rise. A large voltage increase, perhaps above 110% of nominal, could cause other electrical equipment to trip. SAE J2894 (SAE 2011) allows EV chargers to trip for voltages above 110% of nominal. The high voltages resulting from such a cascade could damage distribution equipment and the remaining load.

Case Study and Methodology

Fig. 1 describes how EVs connect with the electrical grid, fuel supply, and driver choices to impact sustainability, resiliency, and grid stability. This case study simulates several vehicle types to observe how combinations of vehicle type and battery capacity interact with electrical demand and user choice (i.e., trip curtailment) to influence emissions, trip completion, and electrical system disruptions. Electrified vehicles use gasoline and/or battery electricity to complete trips, but that electricity comes from the grid thus impacting both grid load (stability) and pollutant emissions (sustainability). The battery degrades with time, reducing its capacity and requiring eventual replacement. That reduction and replacement influences the vehicle's sustainability. From a resiliency perspective, vehicles are used to complete the desired travel of drivers, but under duress (fuel and/or electricity outages) drivers may curtail trips. Through electrification, a fuel-limited vehicle may improve resilience by completing more trips than with fuel alone.

The research reported in this paper examines EVs for the following: (1) sustainability performance using LCA, (2) resilience to gasoline supply disruptions over a 5-day period, and (3) effect

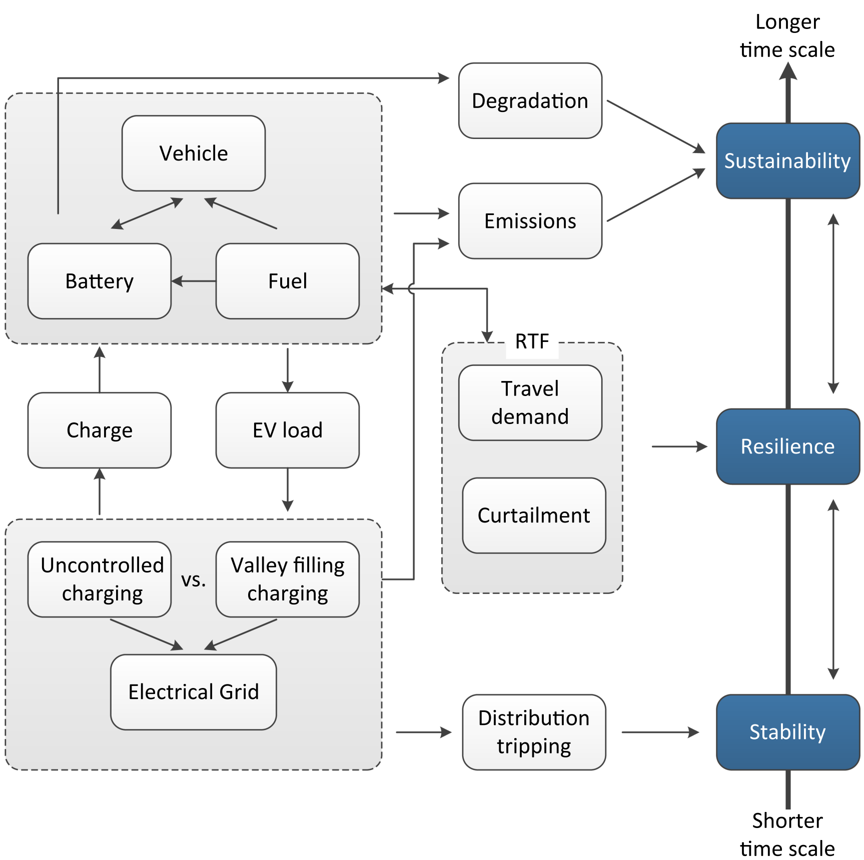

Fig. 1. Research reported in this paper examines the coupled dependencies between EVs and the electrical grid, focusing on the implications for sustainability, resilience, and electrical grid stability

on the electrical distribution network stability. While several studies have examined the lifecycle performance of EVs, the research reported in this paper incorporates a model of battery degradation based on laboratory measurements of battery cycling, and accounts for the long-term shift away from electricity towards gasoline that occurs during that degradation process. The resilience study conducted in the research reported in this paper explores how gasoline shortages impact the capacity of a vehicle to complete its required daily trips, extending previous resilience research. Finally, two vehicle-charging algorithms [(1) valley-filling, and (2) uncontrolled] are evaluated with varying levels of EV penetration to determine their effect on electrical grid stability.

The sustainability, resiliency, and grid stability evaluations rely on shared variables and parameters, but the case studies are examined independently since their timescales are vastly different. All models utilize vehicle-charging algorithm information. The grid stability study conducted in the research reported in this paper uses the ratio of EV load to background electrical load on a millisecond basis. The resiliency study of the research reported in this paper examines day-to-day trip completion subject to charging constraints. The sustainability model evaluates pollutant emissions from electrical charging during the course of 1 year along with vehicle production burdens.

Vehicle Charging Algorithms

Several studies have adopted rule-based charging algorithms to manage EV load and evaluate its impacts on the grid (Elgowainy et al. 2010; Hadley and Tsvetkova 2009; Kintner-Meyer et al. 2007). Most found that coordinated charging is needed; otherwise the aggregate load in peak hours may increase and adversely affect grid reliability. Several studies have reported sophisticated schemes for EV charging, including centralized optimization problems with various objectives, such as valley-filling (Ahn et al. 2011; Lemoine et al. 2008), coordination with combined heat and power (Galus and Andersson 2008), and using EVs as grid reserves (Foster and Caramanis 2010; Han et al. 2010). However, these do not provide implementable algorithms to charge EVs as they often treat the whole EV fleet as one large battery and do not consider attributes of individual vehicles, such as the plug-on/plug-off time and state of charge (SOC). The literature also describes decentralized resource allocation methods for demand response (Burke and Auslander 2009) and EV charging (Ma et al. 2010). However, their practicality is in question as they require massive two-way communications and some require iteration (Maheswaran and Basar 2001). For real-time implementable schemes, dual tariffs are now available that incentivize late-night charging (DTE Energy 2014; Southern California Edison 2014). However, dual tariffs cause an undesired load increase for large EV fleets when the low-price window starts (Lopes et al. 2009a, b). Another real-time implementable scheme is the on/off control for regulating thermostatic loads (Callaway 2009; Goel et al. 2010; Short et al. 2007), one of which has been extended to control EV charging (Callaway and Hiskens 2011). The literature suggests that hierarchical and partially decentralized algorithms are more appropriate for EV charging (Callaway and Hiskens 2011).

The research reported in this paper utilizes an EV valley-filling charging control algorithm that uses idle generating capacity in evening hours to charge a large number of EVs on the Michigan grid. The control algorithm objective is to avoid grid congestion while fully charging all EVs. Vehicle-to-grid (V2G) power flow is disallowed due to the concern that frequent cycling will reduce the battery life.

The algorithm is based on previous research (Ahn et al. 2011; Li et al. 2013), and is summarized in this paper. It consists of an EV fleet model and a grid model. The fleet uses three probability distributions [(1) plug-on time, (2) plug-off time, and (3) battery SOC at plug-on] to describe the EV population. The three probability distributions are derived from vehicle use pattern data (FHWA 2009). In the grid modeling, the hourly load data from the area serviced by DTE Energy [Federal Energy Regulatory Commission (FERC) 2009] is used to represent the nominal non-EV load on the grid. The charging control algorithm adopts a partially decentralized structure, so that its implementation does not require excessive computation and communication. At the global level, an SOC threshold command is calculated and broadcast to all EVs as the basis of charging level. At each charger, the local controller considers two individual EV attributes [(1) battery SOC, and (2) plug-off time] to calculate the final charging power in a decentralized fashion, in that the EVs with lower SOC or early plug-off time should have a higher priority to receive charging. The algorithm allows most EVs to fully charge. In addition, the grid-level objective valley-filling is achieved.

An uncontrolled charging algorithm is also examined, which allows vehicles to fully charge overnight. This returns each vehicle's SOC to 100% each morning.

Grid Stability with EVs

The electrical grid stability portion of the case study focuses on the grid's local distribution response to load variations associated with vehicle charging coupled with an electrical tripping event. Table 1 summarizes the scenarios examined in these analyses.

In a recent study, an analysis tool was presented that determines a critical EV charging load based on the non-EV load on a distribution feeder (Kundu and Hiskens 2014). As the EV charging load fraction increases the likelihood of postdisturbance voltage rise increases.

A voltage sag often results from a transmission grid fault and can affect residential feeders attached to that grid. To model the effect of EV chargers tripping on the voltage profile of the transmission grid, a model of the transmission grid needs to be considered along with a model for the residential feeder. In the research reported in this paper, the conventional IEEE 39-bus system (IEEE 10 Generator 39 bus system model) is considered as the transmission grid, while a modified IEEE 34-node system (Kundu and Hiskens 2014) is considered as the residential feeder; see the "Supplemental Data" section for diagrams and further details of those systems. In the analyzed case, a fault in the transmission grid causes a voltage sag impacting the residential feeder.

Table 1. Electrified Vehicle and Electric Grid Properties for Grid Stability Case Study

Electrified vehicle/grid parameters	Scenario settings 1	Scenario settings 2
Electrified vehicle charging algorithm	Uncontrolled	Valley-filling
Electrified vehicle penetration (%)	10–50	10–100
Background load, DTE 2009 FERC form 714 filing, as per the Federal Energy Regulatory Commission	Minimum load day Average load day Maximum load day	Minimum load day Average load day Maximum load day

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Electrified Vehicle Resiliency

In the context of this case study, resiliency is approached much like the work in Marshall et al. (2015), but the research reported in this paper examines the vehicle, not the household level. Resilience, in this context, is only relevant in the context of a disruption from normal operation, such as a weeklong gasoline outage. Vehicle trip information is obtained from the 2009 National Household Travel Survey (NHTS; FHWA 2009), and simulations of fuel/battery usage are based on that information. Trips are curtailed based on their purpose, and knowledge of how much fuel/battery is both available and required to complete necessary trips. In the research reported in this paper, necessary trips are considered those that are either to travel to or from work or school, termed mandatory trips (all others are termed discretionary). This idealization can be critiqued, but it allows a consistent method for simulating potential responses to emergency-like events, which may induce fuel shortages. Other methods of measuring resilience would be to determine completed trips against potential trips of any type, or perhaps considering trip schedules that do not include work or school, which might be canceled in an emergency situation.

The metric realized travel factor (RTF) is used to describe the effectiveness with which mandatory trips are completed (Marshall et al. 2015). Trips that are completed during the simulation are realized, so to speak. The RTF is the ratio of realized mandatory trips to all mandatory trips. This can also be thought of as a so-called trip completion rate.

The NHTS provides a detailed accounting of personal travel in the United States (FHWA 2009). This study considers a Monday–Friday fuel supply disruption, and extracts those trips from the data. Two thousand vehicles (8,500 trips) are randomly selected from that subset of vehicles to reduce simulation time. A two-sample Kolmogorov–Smirnov test compares the sampled versus original data to ensure consistency of trip times (time $= 0$ h, $p = 0.1315$), and departure time (time $= 0$ h, $p = 0.1930$). Details on how NHTS data were extracted for the research reported in this paper can be found in the "Supplemental Data" section and in Marshall et al. (2015).

A distinction must be described between vehicle trips and tours and how that is utilized during simulation. A vehicle trip constitutes any travel taken by a vehicle between any two locations. A tour is a chain of trips that must begin and end at home. Furthermore, a mandatory tour is any tour that contains any trips that go to work or school.

Tour curtailment is based on the amount of fuel and battery charge available, the tour type, and the tour's distance. So-called normal curtailment is based on a 1-day outlook, assuming that the driver has no knowledge of the potential disruption's duration. In a maximum curtailment scenario, all discretionary trips are avoided throughout the duration of the disruption.

The resilience study of the research reported in this paper couples with the electrical grid model to determine the SOC of each vehicle in the data set. At the end of each simulation day the vehicle battery is recharged based on the charging algorithm. The valley-filling algorithm may not completely charge all vehicles, while uncontrolled charging will fully charge all vehicles.

Five types of vehicles are considered, i.e., a CV, two PHEVs, and two BEVs. The PHEV and BEVs are modeled after production vehicles and are termed PHEV16 km, PHEV64 km, BEV161 km, and BEV483 km to correlate to the nominal distance, in miles, that they can travel on battery electricity. Table 2 contains detailed information about the vehicles. The CV and the gasoline portions of PHEV travel are assigned a gasoline distance budget. Table 3 presents the gasoline budgets examined, as well as the percent penetration of vehicles in the market. The gasoline budget does not necessarily represent onboard gasoline, but gasoline available to the vehicle, suggesting that there may be some limited fueling stations available.

Table 2. Vehicle Design Characteristics Used for All Case Studies, Derived Based on Details of Production PHEV and BEV

Vehicle type	All electric range [km (mi)]	Battery capacity (kWh)	Efficiency [kWh/100 km (kWh/100 mi)]
Conventional vehicle	Not applicable	Not applicable	Not applicable
PHEV16 km (PHEV10)	16 (10)	4.4	18 (29)
PHEV64 km (PHEV40)	64 (40)	16	22.5 (36)
BEV161 km (BEV100)	117 (73)	24	21 (34)
BEV483 km (BEV300)	426 (265)	85	20 (32)

Table 3. Realized Travel Factor Study Scenarios Describing Initial Gasoline Budget and EV Market Penetration, Initial Battery SOC Was 100%

Vehicle parameters	Parameter values
Initial gasoline budget [km (mi)]	{0, 80, 161, 241, 322, 644, 966, 1287, 1609, 3219}
Plug-in hydrid electric vehicle penetration (% fleet)	{2, 4, 6, 8, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100}

Electrified Vehicle Sustainability

Metrics

To evaluate sustainability, the use-phase emissions of each vehicle are calculated and combined with vehicle and battery production emissions to determine lifecycle emissions. Several previous studies examine production emissions for the vehicle and the battery (Hawkins et al. 2013; Samaras and Meisterling 2008; Sullivan and Gaines 2012). The research reported in this paper considers GHG, NO_x, and SO_x emissions; however other impacts such as human toxicity, freshwater ecotoxicity, freshwater eutrophication, and metal depletion are also important and likely to increase due to vehicle electrification (Hawkins et al. 2013). The "Supplemental Data" section contains details for the production phase emissions used in the research reported in this paper. The majority of the vehicle's lifecycle emissions occur during the use phase, and consist of gasoline combustion, and the associated fuel combustion to generate electricity. The effect of battery degradation is also considered, and possible replacement, on vehicle lifecycle emissions. A 10-year lifetime is considered, 7,300 charge cycles (charging and discharging are considered separate charge cycles), for the vehicle.

Battery Degradation

To fully realize the purported benefits of vehicle electrification it is critical to understand the degradation mechanisms of the batteries and managing them optimally. This requires models that are proper (Ersal et al. 2008) for their intended use and are based on carefully designed experiments. The research reported in this paper focuses on $LiFePO_4$ battery chemistry as one of the main battery chemistries considered for vehicle applications. Prior work has performed health experiments for this battery chemistry (e.g., Forman et al. 2012; Peterson et al. 2010; Wang et al. 2011). In the research

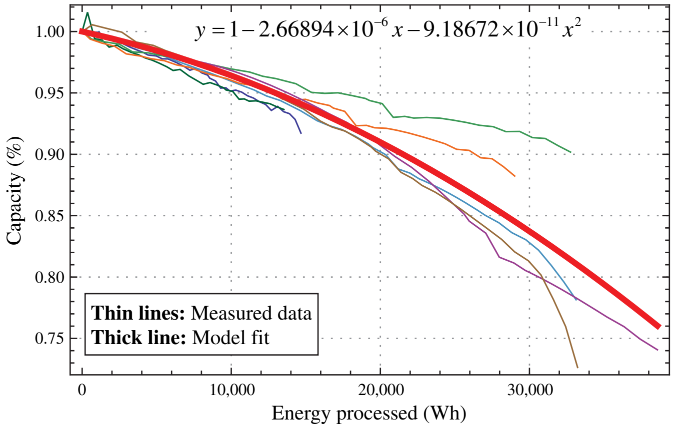

Fig. 2. Battery degradation model using cyclical charge–discharge test data for APR18650M1A battery (A123)

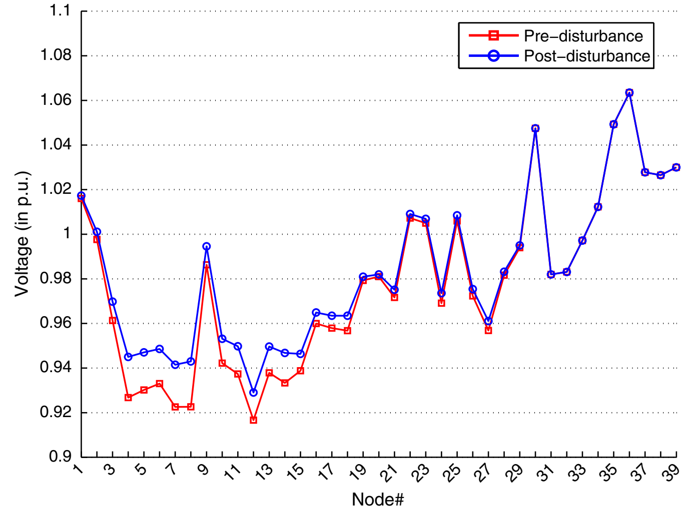

Fig. 3. Voltage on IEEE-39 grid in predisturbance and postdisturbance scenarios given voltage drops at Nodes 4 and 5

reported in this paper the data collected in Forman et al. (2012) is leveraged due to the optimal design of the experiments, but use an energy-processed modeling approach (Peterson et al. 2010) for its simplicity to incorporate battery degradation into lifecycle analysis. From a lifecycle perspective, battery degradation leads to increased PHEV fuel usage and reduces the amount of electricity used per charging cycle for the battery.

For battery degradation modeling, the APR18650M1A battery manufactured by A123 Systems was cycled over 429 days using the optimized set of trials (Forman et al. 2012). The results, Fig. 2, use a second-order polynomial of the form $y = 1 - a_1 x - a_2 x^2$ to fit energy processed versus capacity, where coefficients a_1 and a_2 are determined using a least-squares approach. This result is consistent with what has been reported in Peterson et al. (2010). However, the data obtained in the research reported in this paper extends beyond that and shows that a quadratic function fits the data better over the lifecycle of the battery. Using this model along with NHTS data, 40% of PHEV64 km batteries are determined to be fully consumed after 10 years (7,300 charging cycles). Details are in the "Supplemental Data" section.

Use Phase Emissions

For the use-phase portion of the lifecycle emissions, four different electricity generation mixes are considered for vehicle charging, all in a Michigan context. Emissions factors for each grid are applied to electricity demand due to vehicle charging, assuming one daily charge for a period of 10 years. Electricity consumption due to charging is based on travel patterns sampled from the National Household Travel Survey using the 2,000-vehicle sample described previously (FHWA 2009). The battery degrades until 80% of full (rated) capacity remains available, after which the battery is replaced, thus that vehicle recovers full capacity. The four grid scenarios considered [(1) nonbaseload Michigan, (2) average Michigan, (3) average coal, and (4) average natural gas] use eGrid data to determine GHGs, SO_x, and NO_x emissions. The data are obtained using simple geographic boundaries for facilities located within Michigan. A 6.47% transmission loss factor within Michigan (USPEA 2012) is assumed. Combustion emissions are combined with upstream emissions of electricity production from *GREET* (Wang 2009). Emissions from vehicular gasoline consumption are comprised of both combustion and upstream emissions and data are obtained from *GREET* (Wang 2009). The "Supplemental Data" section contains emissions factor details for gasoline and electricity.

Results and Discussion

Vehicle Charging

The valley-filling EV charging control algorithm utilizes idle generating capacity in the late evening to charge a large number of EVs, so that the aggregate load can achieve valley-filling. The algorithm allows the majority of EVs to fully charge without excessive computation within the vehicle or communication of data between vehicles and the grid. In a simulation using 2.4 million PEV40 vehicles (30% penetration) on the hypothetical Michigan grid during its lowest load day, the average battery SOC after charging was 95%. All vehicles were charged to at least 90% of their capacity. This varies depending upon vehicle type, penetration, gasoline budget, and the background electrical demand; greater detail can be found in Li et al. (2013). The uncontrolled charging algorithm charged vehicles overnight to 100% SOC. This was viable up to 50% vehicle penetration due to electrical supply constraints.

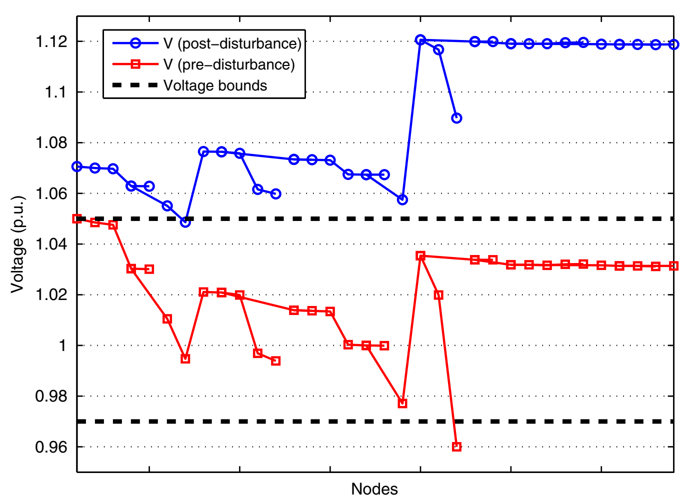

Fig. 4. Voltage on IEEE-34 feeder during predisturbance and postdisturbance scenarios with bounds indicating safe operating conditions

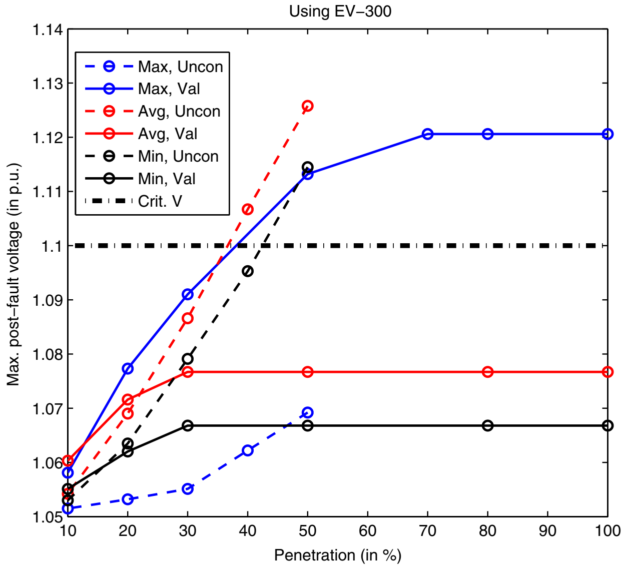

Fig. 5. Overvoltage at varying penetration levels BEV483 km (BEV300s) (most aggressive vehicle scenario) and under different loading and charging scenarios

Grid Stability with EVs

Figs. 3 and 4 show a postfault overvoltage due to tripping of EV chargers. For this case, the base load curve of August 2, 2009 (maximum load scenario) is considered along with the valley-filling charging algorithm. Simulations are performed with an EV penetration level of 70%, and at the lowest point of the load valley. It is assumed that the load profiles (both EV and non-EV) at Nodes 4 and 5 are in accordance with the same pattern. Due to a voltage sag, the EV load is lost simultaneously at Nodes 4 and 5 causing a rise on the transmission grid (Fig. 3) as well as the feeder (Fig. 4). Voltage rise due to EV load drop is small at the transmission level, but the effect is large at the distribution level, where maximum node voltage is 1.12 V/unit.

This simulation is conducted with varying EV penetration levels, base load scenarios (maximum load day, minimum load day, or average load day), and charging schemes (uncontrolled or valley-filling) to determine the maximum postfault voltage for each case. Fig. 5 shows the collection of those results. Uncontrolled charging does not consider vehicle penetrations above 50% since the electrical demand exceeds capacity.

Except for penetration levels less than 30%, the valley-filling algorithm typically performs better than the uncontrolled charging algorithm in terms of postfault voltage rise. Only during the maximum load day does the valley-filling algorithm fare worse than the uncontrolled charging scheme. This is because the ratio of EV load to total grid load becomes very high in that scenario compared to the other scenarios; the drastic load peak occurring in that scenario facilitates this. As penetration level increases the overvoltage condition worsens faster in the case of uncontrolled charging, while in the case of valley-filling the overvoltage situation ultimately saturates. Using valley-filling, the maximum load day has the worst overvoltage conditions, whereas for uncontrolled charging, the maximum load day is the safest. This suggests that for grid stability purposes a blended operation should be adopted within the valley-filling algorithm that considers the ratios of EV to non-EV load.

Electrified Vehicle Resiliency

A daily RTF is calculated for five vehicle types [(1) CV, (2) PHEV16 km (PHEV10), (3) PHEV64 km (PHEV40), (4) BEV161 km (BEV100), and (5) BEV483 km (BEV300)], at several different levels of market penetration. The gasoline budget for each vehicle is the same at the start of the first day, but vehicle usage reduces that capacity over time. Fig. 6 shows the RTF of the different vehicle types with their differing gasoline budgets at the end of the 5-day outage. The left-hand bar within each vehicle set presents the baseline scenario (no curtailment of discretionary trips), while the right-hand bar presents the maximum curtailment scenario. The RTF results for the 5-day outage considering normal curtailment (i.e., 1-day outlook) were nearly identical to the baseline results, and are not presented. Interestingly, the difference between an uncontrolled and valley-filling approach to battery charging is less than 1%, highlighting the adequacy of valley-filling in the context of resiliency.

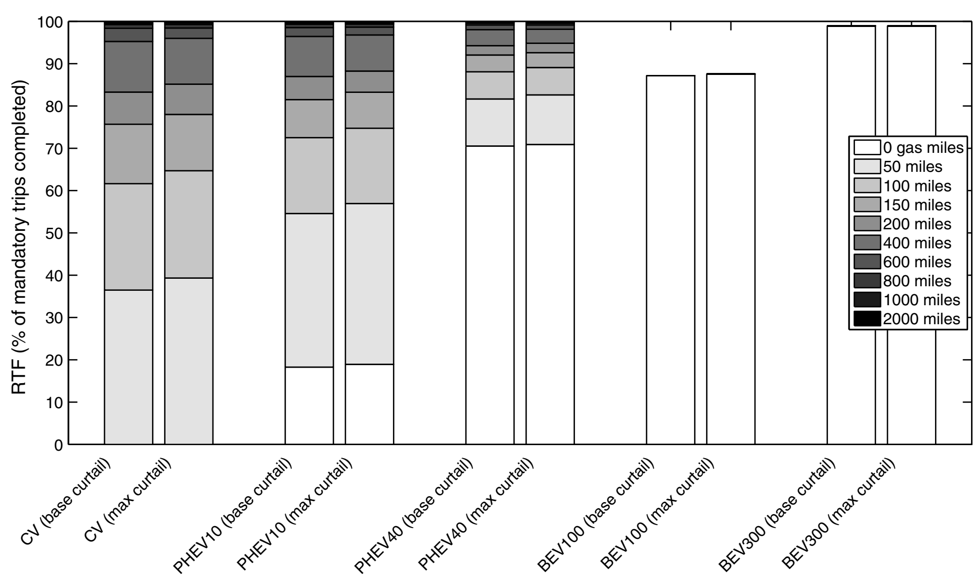

Fig. 6. Realized travel factor for daily driving in event of gasoline disruption; legend shows the gasoline miles available to each vehicle in the sample population for a 5-day scenario

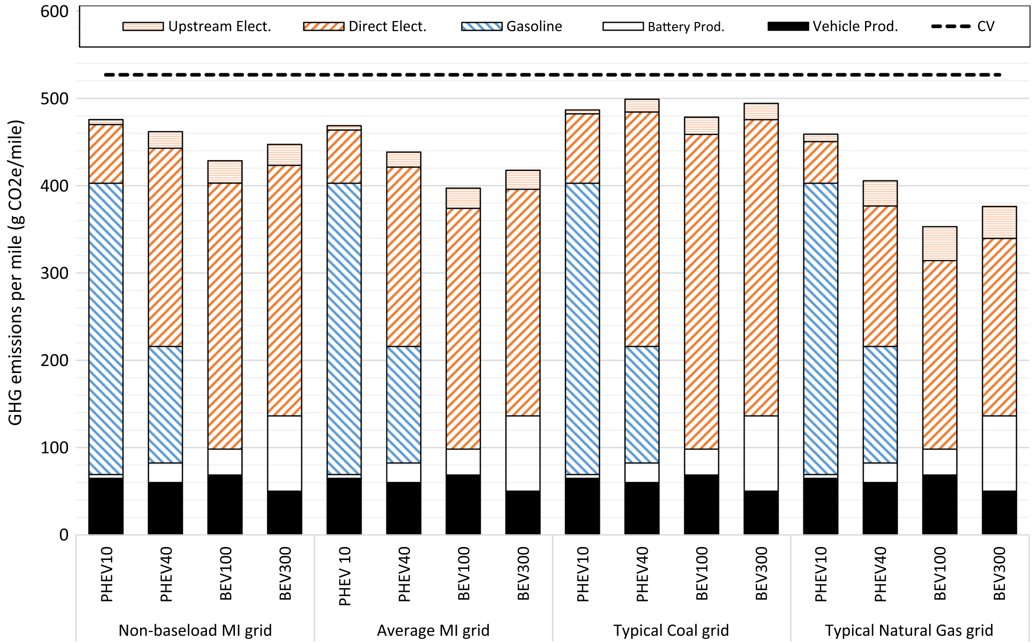

Fig. 7. Greenhouse gas emissions for each vehicle for each of the four grid scenarios by production and use phases

The results show that the effect of vehicle electrification on RTF is far greater than behavioral adjustments using the curtailment rules considered. For instance, the CV with a 5-day gasoline budget of 80 km (50 mi) achieves 37% RTF in the baseline scenario and 39% in the maximum curtailment scenario. But, the PHEV16 km (PHEV10) baseline scenario achieves an RTF of 55% even without trip curtailment. Thus, even a modest electrification of the vehicle yields a significant increase in system resiliency. As behavioral adjustment is added in tandem with technology there are modest increases in RTF. Finally, RTF improvements have diminishing returns with respect to increased fuel availability.

The trip curtailment approach considered in this paper is only one of many possibilities. In real crisis situations causing prolonged fuel shortages it is possible that workplaces or schools will be closed; or that individuals will seek to carpool, take public transit, walk, or bike in lieu of driving. Such alternative possibilities were not considered in the research reported in this paper, and their inclusion is left for future research.

Electrified Vehicle Sustainability

The lifecycle GHG, SO_x, and NO_x emissions are calculated over the 10-year life of the vehicle, including vehicle and battery production, as well as upstream and combustion emissions for both gasoline and electricity. In addition, results include battery degradation and replacement during the lifetime of the vehicle.

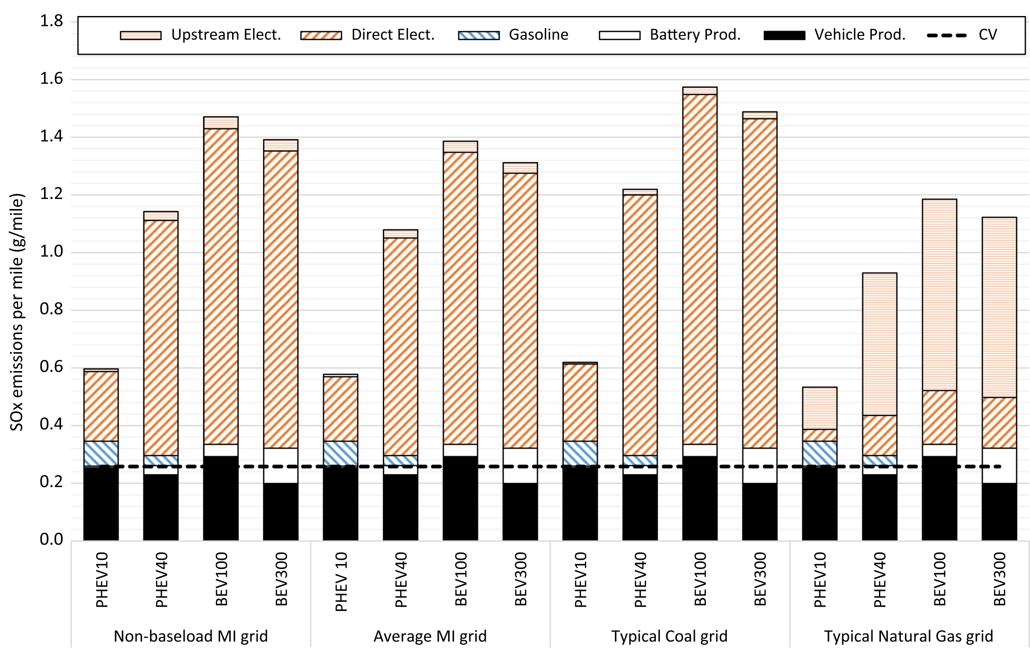

Fig. 8. SO_x emissions for each vehicle for each of the four grid scenarios by production and use phases

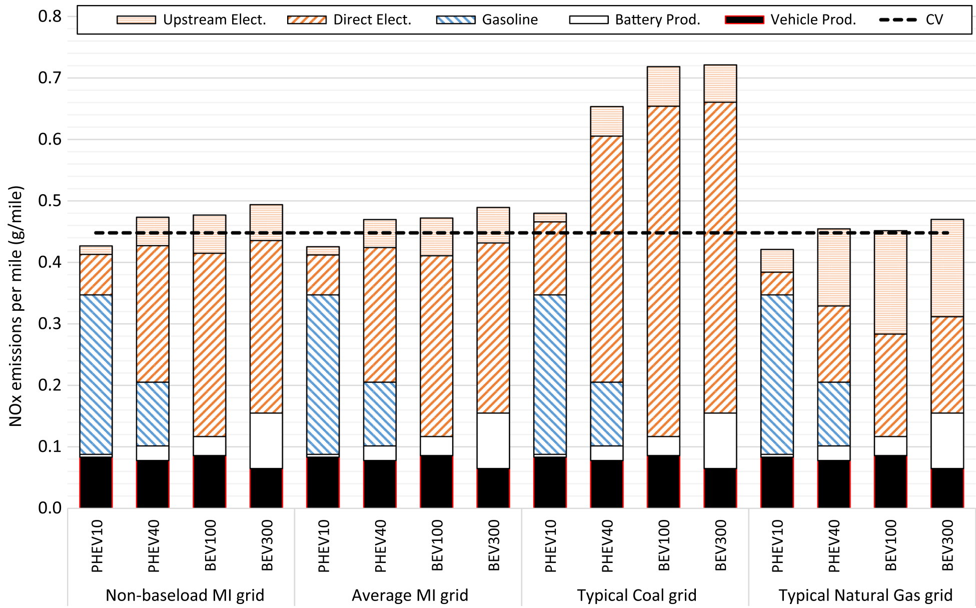

Fig. 9. NO_x emissions for each for each of the four grid scenarios by production and use phases

Fig. 7 presents lifecycle GHG emissions on a per-mile basis for each vehicle considering lifecycle phase, and charging location. The black, dotted line represents the lifecycle performance of a comparable CV, accounting for its production emissions, and gasoline combustion and upstream emissions. All electrified vehicles outperform the CV for GHG emissions using the grid assumptions of the research reported in this paper, but higher emitting grids could cause electrified vehicles to perform worse than a CV. The PHEV64 km (PHEV40) outperforms the PHEV16 km (PHEV10) for GHG emissions reductions since it uses more electricity than the PHEV16 km (PHEV10). The two BEVs are less emitting of GHGs than the other vehicles.

Figs. 8 and 9 illustrate the findings for SO_x and NO_x emissions, respectively. The trends in Figs. 8 and 9 are generally opposite from the GHG trends. Typically, SO_x and NO_x emissions are greater from EVs as compared to a CV. In addition, a larger battery increases those pollutant emissions since the vehicle uses more electricity, and due to battery production. An important caveat is that NO_x and SO_x are both local and regional pollutants, so that their increase, while seemingly large (especially for SO_x, since gasoline is regulated to contain very little sulfur), may not translate to particularly adverse human health or environmental impacts if the electrical plants are distant from population centers and remain within EPA mandates.

Broadly, a larger vehicle battery results in a higher percentage of electrically driven kilometers (miles). Increases in electric kilometers (miles) driven, and the associated daily recharging, shift the emissions source to the respective electricity generation grids and away from gasoline combustion. The emissions for each grid are in accordance with the trend in emissions factors. These findings reinforce the importance of the electricity generation portfolio and the vehicle's battery size in environmental assessment seen in prior literature (Elgowainy et al. 2010; EPRI 2007; Hawkins et al. 2013; Samaras and Meisterling 2008; Sioshansi and Denholm 2009; Sioshansi et al. 2010). A sensitivity analysis was conducted assuming a 257,500-km (160,000-mi) vehicle lifetime, and the results show that increased kilometers (miles) lead to increased battery replacements, but overall, the per-kilometer (per-mile) emissions of all pollutants are reduced for all vehicles across all electrical grids. Details of this analysis can be found in the "Supplemental Data" section.

Conclusions

The research reported in this paper examined the sustainability, resiliency, and stability effects of the coupled infrastructures of the electrical grid and transportation through EVs. The case study analysis indicated that there are dependencies between sustainability, resiliency, and stability, and that these dependencies must be modeled across very different timescales. These timescale differences allow for a predominantly decoupled analysis of each domain's phenomena, but model integration (variable, parameter, and scenario consistency) is imperative for more meaningful results. Thus, as long as all modeling assumptions are consistent, the research reported in this paper allows for independent simulation of sustainability, resiliency, and stability results, as long as the supporting data in those studies are determined through an overarching scenario (which in this case is the vehicle charging algorithm).

For instance, while the (1) stability effects examined in this paper occur at the millisecond scale, and (2) resilience occurs at the day scale, the two are intimately coupled through the hourly charging algorithm. That algorithm determines the ratio of EV load to background load, thereby influencing the grid stability. The charging algorithm also determines vehicle SOC, which impacts vehicle resiliency. In addition, the charging algorithm has a long-term effect on sustainability since valley-filling methods utilize a different set of electrical assets (baseload) than uncontrolled (nonbaseload) due to the time of charge, and the emissions of those assets can vary greatly.

This paper only examined a few, well-defined concepts of sustainability, resilience, and stability subject to very specific scenarios. The results suggest that each topic may be studied in absence of the others; however, doing so may not only give an incomplete view of that topic, but also neglect important impacts within other topics. For example, the research reported in this paper uses a valley-filling algorithm due to its ability to keep grid loads from exceeding peak demand while still charging vehicles. In this regard the algorithm

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worked well, but it was discovered that such an approach creates a distribution-level grid stability problem at high penetrations of electrified vehicles on high demand days. It was also discovered that the RTF associated with EVs charged using the valley-filling algorithm varied little from an uncontrolled charging scenario, but this could not be known a priori.

Electrical and transportation infrastructures can be directly coupled through EVs, and at low levels of penetration this coupling has dramatic benefits to resilience (RTF increases due to electrification), and sustainability (GHGs decrease, while SO_x, NO_x increase with electrification) while not causing grid stability problems regardless of the charging algorithm. However, as the penetration level of EVs increase the potential for grid stability problems increases, while having little effect on resilience or sustainability. This paper highlights the importance of evaluating the infrastructure systems in their coupled form across multiple timescales in order to capture effects that may not be obvious in absence of one another. The framework developed in the research reported in this paper to explore the interplay between system performance metrics (e.g., resilience, sustainability, and grid stability) across timescales can be modified to study other complex infrastructure systems. An important next step in the research reported in this paper is to examine how a constrained electrical system (i.e., blackout and brownout conditions) can impact the transportation resiliency with an electrified fleet. Presumably, EVs will serve to highly constrain travel in the absence of charging infrastructure.

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Supplemental Data

Supporting information, including Figs. S1–S7 and Tables S1–S13, is available online in the ASCE Library (www.ascelibrary.org).

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