Project Description

1 Vision Statement

This research studies the interactions between transportation systems and power systems, coupled by plug-in electric vehicle (PEV) user behaviors in urban environments. In particular, we seek to explore the nature of this interaction from a novel perspective that implicitly includes human behaviors with its associated uncertainties in the loop. We then develop sustainability-oriented, cyber-enabled tools for analyzing, designing, monitoring, and managing urban vehicle-grid systems.

As cities grow, mobility and energy networks are becoming increasingly stressed. In particular, electrified transportation is both diversifying and merging these systems into a complex interconnected infrastructure, as shown in Fig 1. PEVs provide energy efficient mobility options and distributed energy storage, yet impose significant electrical loads and limited travel range. This growing technological shift fundamentally alters how we must design, monitor, and manage the transportation-electricity infrastructures. In parallel, the ubiquity of internet-connected devices, big data, and real-time automation enables a new generation cyber-enabled sustainability-focused infrastructure management technologies.

This research seeks to comprehend the fundamental interconnected network dynamics of transportation-power-human behavior systems engendered by an expanding PEV fleet. To this end, this project pursues a cross-disciplinary, sustainability-driven vision to model the interactions between the transportation system, electric transmission-circuit system, and PEV driver behavior. Our goal is to understand congestion, in both the highway and electric grid, evolving over both spatial and temporal dimensions. We consider spatial dynamics at the metropolitan scale (e.g. San Francisco Bay Area) and temporal dynamics at the tens of minutes scale. Mathematical models of each network will be supported and enriched by available data and simulation platforms, such as activity-based micro-simulation of mobility calibrated on California house-

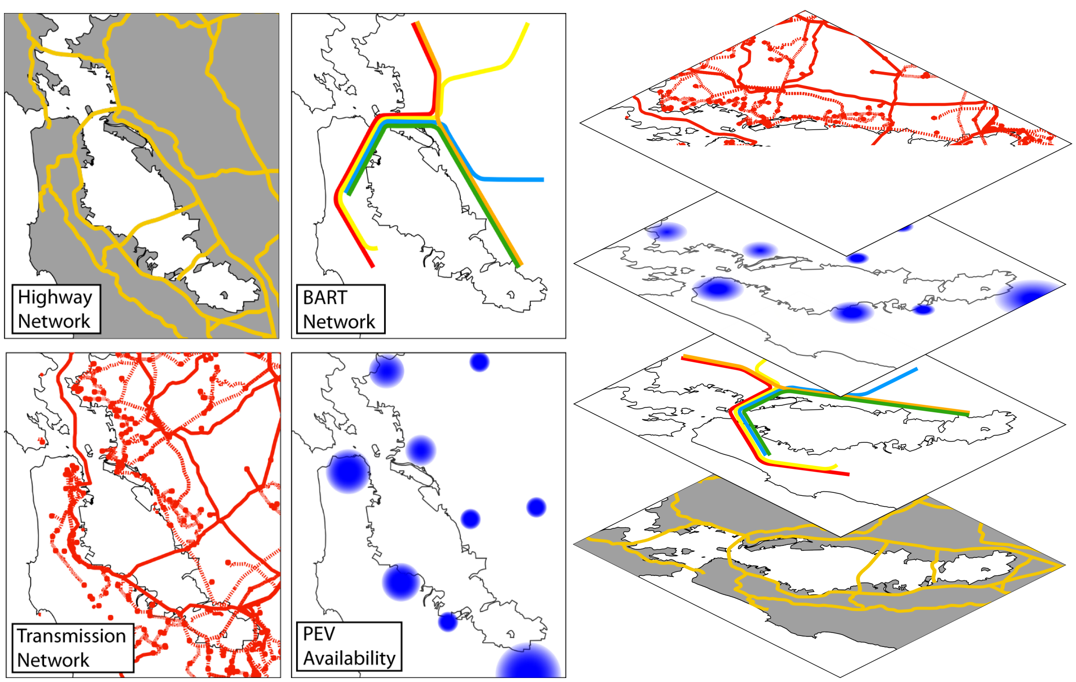

Figure 1: The transportation (highway & BART light-rail) and power system (transmission circuit shown) networks have been traditionally examined separately. PEVs will couple these networks into a complex interconnected system that requires new modeling and management tools to ensure sustainable operation.

hold travel survey (CHTS) and cellular call data records (CDRs), and advanced metering infrastructure (AMI). In addition, we seek to quantify the flexibility of PEV drivers to shift charging/commute demands in time and space to alleviate traffic and power system congestion, via appropriate incentive mechanisms. We anticipate more flexibility in time shifting, and less in spatial shifting. Survey data for these models will be generated from MyGreenCar [1], a smartphone app used for vehicle fuel economy predictions. Armed with mathematical models of transportation, electric grid power flow, and behavior, we pursue several focused design questions. These include spatio-temporal estimation of flexible PEV energy storage, dynamical properties of network congestion, optimal siting of public charging stations, and controllability of PEV drivers to shift mobility/power demand for congestion management.

Our vision is that a modeling & simulation platform for the complex interactions of transportation, power systems, and PEV driver behavior will be invaluable for the analysis, design, monitoring, and management of a sustainable urban vehicle-grid infrastructure system. This holistic vision challenges existing computational methodologies by utilizing real-time distributed data streams, incorporating stochastic driver behavior, and predicting mobility/power flow dynamics in both space and time at the city-scale.

2 Background and Significance

Transportation is responsible for over 30% of global energy consumption and nearly 72% of oil demand. The volatility of oil prices over the past half-century, the political instability of oil producing nations, and the environmental damage caused by fossil-fueled vehicles has motivated governments to view electric transport as essential to economic growth, energy independence, and greenhouse gas reduction [2]. In California, for example, Gov. Jerry Brown set a target of 1.5 million zero emissions vehicles on California roads by 2025 [3]. If California achieves this goal via PEVs, then the total PEV fleet would comprise over 30 GW of load. This accounts for 60% of the 2013 summer peak load [4, 5]. The U.S. market share of passenger PEVs increased from 0.14%, 0.37%, 0.62%, to 0.73% of new car sales during years 2011-2014 [6]. Although relatively small in aggregate, these vehicles are concentrated in urban centers and exhibit considerable localized power system stress.

Simultaneously, states have enacted Renewable Portfolio Standards (RPS) that require a percentage of power generation to be supplied by eligible renewable resources, such as photovoltaics and wind (e.g. 33% by 2020 in California) [7]. The critical challenge of renewables, however, is mitigating the intermittency of available resources. Under current infrastructure management practices, 33% renewable penetration would require 3.3 GW of increased reserve capacity [8], thereby inflating the economic cost of generation.

If left unmanaged, PEV penetration and renewable integration will require significant infrastructural improvements, impose non-sustainable economics, and significantly threaten the resilience of both transportation and power systems. However, if managed appropriately, the PEV fleet provides a significant fast-ramping energy storage and clean mobility resource to enable efficient transport, renewable penetration, and revenue streams to PEV drivers in exchange for flexibility. The significant intellectual and practical challenge, however, is that transportation and power systems have traditionally been considered decoupled network systems. A careful understanding of the intimate interconnections between these networks, coupled by PEVs, is paramount to ensuring sustainable urban vehicle-grid systems.

In this proposal, we focus on developing computational models for the interdependence between transportation networks, power system transmission circuits, and PEV driver behavior. This integrated model enables novel analyses of traffic/power system congestion, PEV driver flexibility, and design tasks that enhance energy, mobility, and economic sustainability. We pursue an integrated intellectual agenda that combines activity-based mobility simulation, spatial analytics and machine learning, systems and control theory, and behavioral modeling. This project focuses on the following technical and sustainability challenges.

2.1 Technical Challenges

Challenge #1: *To what extent and how are the power and transportation systems coupled? What is an appropriate modelling framework required to reflect the structural and dynamical properties of interconnected transportation-electrical-human networks in sufficient detail?*

Transportation systems analysis [9] and power system analysis [10] are two traditionally disparate fields of research and business. PEVs couple these systems by consuming energy over the transportation network, and receiving energy from the power network. The structure and dynamics of this coupling includes human behavior in the loop and is therefore more subtle as compared to what is described by state-of-the-art network science [11]. This research integrates recent advancements in data-rich mobility and grid modeling into a combined transportation-electricity network model with behavioral models of PEV owners.

PEVs serve as distributed, mobile energy stores. The spatio-temporal evolution of PEV energy is generally unknown, but is highly predictable by examining daily routines of PEV owners [12]. To this aim, we adopt an activity-based approach to model and simulate human mobility. We focus on reproducing a typical day scenario and providing reliable short to medium-term forecasts (along with associated uncertainties) of the destinations of PEVs distributed over a metropolitan area. Its accuracy depends on daily routines (work commute), secondary destination choices of the individual PEV users, and the current traffic conditions in the region. These processes are subject to large uncertainties due to limited data used in traditional modeling approaches. We leverage the detailed activity-based multimodal simulation of urban mobility, the *SmartBay*, built by the Co-PIs and calibrated on CHTS and cell phone data records. Built on the MATSim platform, it produces a realistic set of daily routines and trajectories for PEV owners that condition the network coupling dynamics. The model operates at the level of individual drivers making particular destination choices, and is ideally suited to incorporate behavioral effects such as range anxiety and responses to charge-shifting incentives. The spatio-temporal evolution of PEVs provides required inputs into grid control algorithms, when properly adjusted for owners' willingness to participate.

Challenge #2: *How flexible are PEV owners to shift their charging and commute, in both time and space? What incentive mechanisms maximize this flexibility?*

Various factors influence PEV charging/travel flexibility. Specifically, the consumer will balance the inconvenience associated with relinquishing control of her PEV with the benefit of the incentive provided by the demand side aggregator. A number of factors affect this balance including: the design of the incentive itself, mobility patterns, the PEV battery state-of-charge, any inconvenience associated with her participation, and a host of attitudes about potential environmental benefits and perceived social norms. Behavioral models of participation, including willingness to participate under different incentive schemes must be developed by characterizing a consumer's utility. This objective is challenging for several reasons, including: (i) very few PEV owners (a self-selected group that is likely not generalizable) currently interact with flexible charging/commute programs (e.g. OhmConnect, BMW i ChargeForward); (ii) large heterogeneity in consumer preferences and utility functions [13, 14]; (iii) critical influences on utility such as range-anxiety that are not yet quantified for such models, (iv) two-way, real-time communication and data processing is novel both to the consumer and developers [15]. Novel behavioral models of PEV owner decision-making will enable effective incentive mechanism design and a reliable quantification of charging flexibility for aggregators (e.g. OhmConnect, PlugShare, and others).

Challenge #3: *Where is the PEV energy storage resource over time, and how much exists? Can traffic and power system congestion be predicted, and mitigated by incentivizing PEV driver charging locations and timing? How does one optimally design and manage these networks for sustainability, e.g. public charging station siting, traffic management, smart charging?*

Given smart meter data, traffic data, and the aforementioned transportation and behavior models, one can predict how the PEV energy storage resource evolves at the city-scale. Processing large distributed data feeds with nonlinear uncertain network models requires new computational methods in state estimation.

Given a spatio-temporal distribution of PEVs, theoretic foundations must be developed to ensure charging behavior is beneficial or at least not adverse to grid reliability and mobility [16]. More interestingly, these foundations should identify and capitalize on opportunities that might enhance performance metrics across transportation systems and the grid. For example, a commuter might be incentivized to park their vehicle at a light-rail station in the city's periphery to support local grid stresses, and then use light-rail into the city's urban center (in exchange for a financial reward). This could potentially ameliorate grid stress and traffic congestion simultaneously. Such interconnections between the power and transportation system networks are currently unexplored, and potentially provide rich opportunities to enhance sustainability across both infrastructures. Network models and control systems theory are ideally suited to examine opportunities revealed in the PEV-coupled transportation-energy nexus. Moreover, it provides compelling context to advance infrastructure & behavior modeling, spatial data analytics, and systems and control theory.

2.2 Research Framework

Figure 2 presents the proposed research contributions as a conceptual framework of three integrated research tasks designed to develop computational tools to analyze and manage urban vehicle-grid systems.

Task 1 will synthesize a computational model for coupled transportation-power system networks, at the metropolitan scale. The transportation system model will be an outgrowth of the SmartBay project, an agent-based simulation model of urban mobility based upon MATSim and calibrated with mobile phone call detail record data. The electrical power system model will consist of a transmission circuit model based upon AC power flow equations. These two urban scale network models will be coupled by hypothetical PEV populations charging at public and private charge stations.

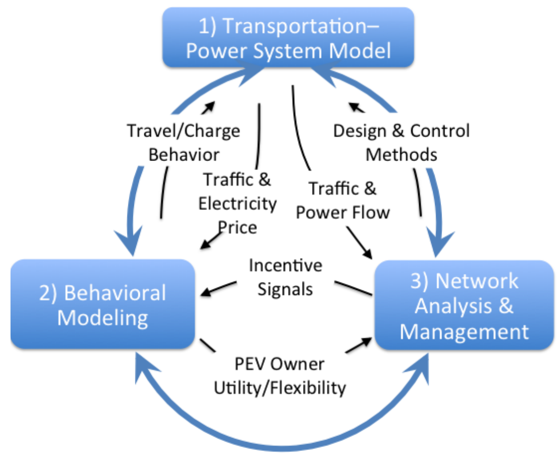

Figure 2: Integrated Research Framework.

Task 2 will examine how drivers interact with vehicle-grid systems. Namely, it will develop behavior models that predict (i) a driver's PEV energy flexibility and (ii) reactions to various incentive mechanisms. These models enable us to quantify the reliable flexible energy storage available in aggregated PEV populations. Since little data exists on consumer participation in smart charging, Task 2 will conduct preference surveys to examine PEV owner response to a variety of incentive models. The MyGreenCar Driver Information System [1] will be used to communicate in a realistic fashion the impact of the decisions on one's personal travel, and the behavior models will estimate key behavioral constructs such as range anxiety.

Task 3 will study the transportation-electricity network dynamics, using the modeling results from Tasks 1 and 2. First, we seek to synthesize an ensemble Kalman filter state estimation algorithm that predicts spatio-temporal evolution of flexible PEV energy provisioned from drivers. Second, we study system theoretic properties of congestion in coupled networks and examine optimal design formulations that optimally site EVSEs to minimize congestion and travel/charge time. Third, we examine the controllability of vehicle/power flow through PEV owner incentive mechanisms.

3 Research Plan

3.1 Task 1: Modeling the Coupled Transportation-Power System Networks

Objectives: This task will develop a data-driven mobility model providing space-time locations of PEVs, and the trip purposes of their owners. Trip purpose is required for integrating the behavioral analysis in

Task 2 that designs charging/commute shifting incentives, and effectively closes the loop in estimating demand management impacts on the coupled system. Both daily mobility scenarios, short/medium term forecasts, and associated uncertainties are required by Task 3 for designing grid control algorithms.

Task 1.1: Activity-based Mobility Modeling with Cellular Data Agent-based micro-simulation is a computational modeling approach that allows handling complex interactions within and between coupled social, environmental and infrastructure systems. An activity-based micro-simulation model of mobility in the San Francisco Bay Area (The SmartBay) is being developed by the co-PI group based on the MATSim platform. MATSim [17, 18] is a well-established open source mobility micro-simulation engine for modeling mobility at the level of individual dwellers ('agents'). It seeks for a user equilibrium that maximizes each agent's personal utility related to accomplishing the prescribed daily activity plan [19]. It does so by solving dynamic traffic assignment along via varying departure times by applying evolutionary optimization for possible re-planning of the sequence and destinations for secondary activities (that is, all other activities besides home, work and school trips).

The baseline SmartBay simulation implements a scenario of a typical working day within all 9 counties of SF Bay Area. It operates a virtual population of about 1 million agents moving on a road network of 96,000 links including all freeways and major arterial roads, as well as all major public transit lines available through General Transit Feed Specification (GTFS) provided by the respective agencies. Population and home-to-work commute demand is adjusted from cell phone records within an ongoing collaboration with AT&T. The frequency of secondary activities (shopping, leisure, social, etc.) and statistics on the composition of tours for secondary trips have been adopted from the model developed by the Metropolitan Transportation Commission of the Bay Area based on the California Household Travel Survey. There are 120,000 venues derived from the Factual API and introduced to the simulation as destinations for secondary trips. Spatial choice model for the secondary home- and work-based trips is calibrated from the cell phone data logs [20, 21]. The model is validated based on the traffic volume counts collected by CalTrans Perfor-

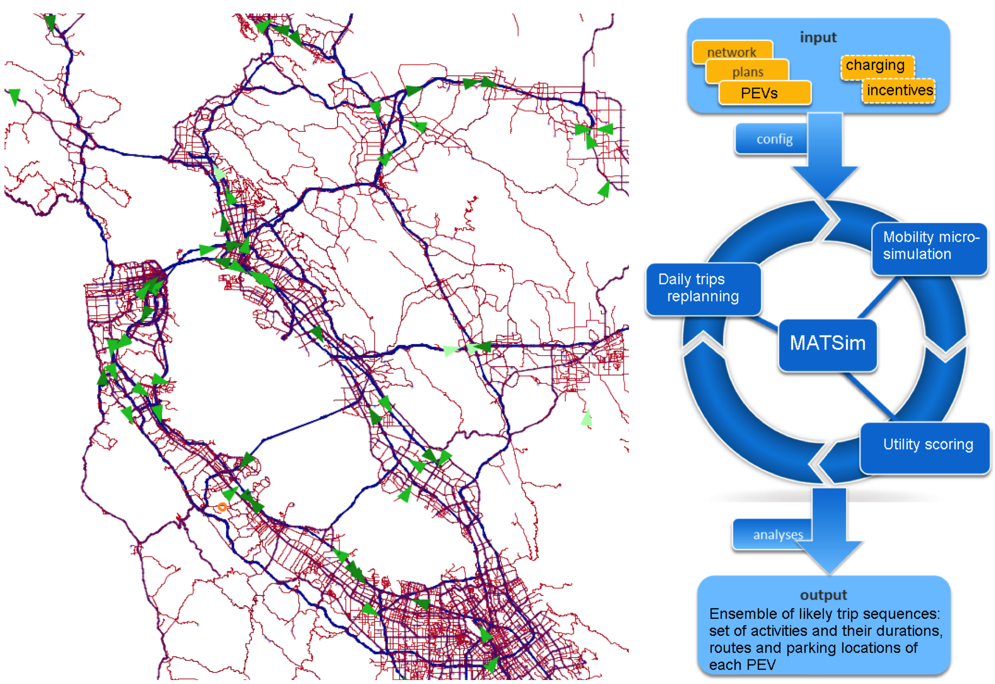

Figure 3: Left: sample from SmartBay scenario run, illustrating the freeway and arterial road networks, public transit BART lines and a sample of vehicles (PEVs) in travel. Right: modelling workflow of imputing agent activity sequences, performing traffic optimization and replanning, and scenario output generation.

mance Management System (PeMS) for all major freeways, as well as the travel times on major routes to match the Federal Highway Authorities model accuracy specifications.

SmartBay produces traffic flows in response to travel demand generated by the agents' desired itinerary, mode, and route. In this task, agents' definitions and utility function will be extended to implicitly include PEV specifics (range anxiety, destinations with charging stations, derived utility from incentives).

Task 1.2: Transmission Circuit Modeling We will quantify the significance of EV mobility and the resulting charging requirements on power system operations with a transmission network model assembled from the Western Electricity Coordinating Council's (WECC) public transmission & generation and load data sets, as well as Pacific Gas and Electric's (PG&E) dataset of lower voltage conductors and substations. With these data we can produce a model with topology of arbitrary resolution (i.e. to the level of individual street addresses). For initial tractability we will assume all PEVs are directly connected to the substations that are electrically nearest according to the WECC and PG&E maps. This will enable us to understand the effects of transmission level and substation bank constraints. We will use publicly reported impedances where available and approximate impedances based on published conductor sizes or capacities and nominal voltages. We will initially solve a simplified DC optimal power flow problem using the WECC load data, assumptions about PEV charging, and generator heat rate and fuel price data taken from the WECC model. As we refine the model, if voltage regulation equipment location becomes available, then we will explore the possibility of solving the simulations with a full AC power flow algorithm.

Task 1.3: Model Integration

Mobility data on the spatio-temporal evolution of PEVs from Task 1.1 will be processed for subsequent use with the transmission circuit model of Task 1.2. The PEV origin-destination and trip-specific routing information, in particular, will be used in the Vehicle-to-Grid Simulator (V2G-Sim) [22, 23] - a Monte Carlo simulator - to generate trip-specific drive cycles for individual vehicle trips. As shown in Fig. 4, V2G-Sim is comprised of coupled sub-models that model the on-road energy consumption and plugged-in charging dynamics of individual PEVs, that in turn will be used to generate temporal and spatial grid-scale impact/storage capacity predictions. This detailed modelling is required to produce accurate inputs for range anxiety disutility terms in Task 1.1, as well as grid control algorithms (Task 3) that ensures the individual mobility needs of drivers are preserved.

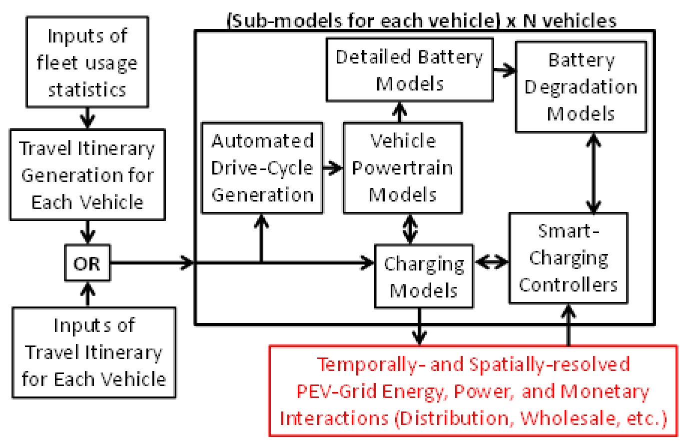

Figure 4: Schematic overview of V2G-Sim, which will be applied to bridge mobility data for vehicles to energy consumption on trips and ultimately to energy interactions with transmission system models [22, 23].

Task 1.4: Uncertainty Characterization and Behavioral Feedbacks Figure 3 (right) illustrates the modelling stages and a replanning cycle of the SmartBay mobility simulation model. Agents (representing conventional vehicle drivers as well as PEV owners) adapt their behaviors in response to current traffic congestion, accessibility of services, charging station availability, and a feasibility to accomplish the assigned daily activities plan. SmatBay utilizes the MATSim engine that applies evolutionary optimization to an ensemble of agents' daily plans. Its essential feature is that an agent can drop an activity out of the daily plan if its execution yields low utility. This becomes extremely important for modeling PEVs, in the sense of accurately representing mobility pattern changes induced by range limitations. In coordination with Task 2.4 we model feedback impacts assocated with demand management strategies in order to evaluate shifting mobility patterns specific to PEVs. This includes adjusting destinations to charging stations, as well as induced demand due to modality shifts. It is essential to include this feedback loop to adequately carry out demand management studies.

Finally, this task will produce estimates of space-time PEV-induced impact/storage availability with corresponding uncertainties by spatially aggregating (using substation zones defined in Task 1.2) over ensembles of individual PEV travel sequences processed by V2G-Sim.

Expected Outcomes:

- Activity-based traffic micro-simulation platform of daily displacements of a given PEV fleet in the area for simulation scenarios (space-time PEV resource availability).
- Transmission circuit power system model, where PEV load/storage is aggregated at substation nodes.
- Uncertainty characterization, resulting from stochastic itineraries and model parameter values, derived from an ensemble of feasible daily plans of each agent representing an individual PEV owner.

3.2 Task 2: Behavioral Modeling of PEV Owners & Incentive Mechanism Design

Task 2 focuses on human behavior, and specifically incentivizing PEV owners to participate in a grid management program. That is, what resources can actually be *realized* from PEV owners and at what cost? The answer requires understanding the factors that influence PEV owners' willingness to accept the provided incentives and change their charging and travel patterns through demand-side management (DSM) services.

Objectives: Develop behavioral models of consumers' participation in demand-side management systems, including responses to different incentive schemes. Evaluate the potential of different incentive programs to optimize the flexibility of PEV resources.

Proposed Effort: This endeavor pursues consumer behavior models in the context of DSM. Specifically, we seek to understand the main determinants of consumers' disutility when relinquishing the control of their PEVs, as well as consumer attitudes towards different incentive schemes. Several factors drive this response, including the mechanism design (amount and form of the incentive), the vehicle usage patterns (daily tour composition and trip purposes), the PEV battery state of charge, any inconvenience associated with participation, and a host of attitudes including environmental stewardship.

One fundamental question is what form of incentive is most appropriate. Example incentive forms include direct monetary payouts, lottery systems, and/or non-monetary social-based awards such as badges. Due to prevailing wholesale electricity market structures and the public good attributes of DSM services [24, 25], incentivizing PEV owners' participation in DSM programs may prove to be a non-trivial task for aggregators. This was previously studied by Co-PI Callaway (as part of NSF award number 1239467) within a scoping study in the context of the Singapore's electricity sector.

It has been experimentally observed that individuals exhibit risk-seeking conduct when presented with lotteries that confer them with small chances of large rewards [26, 27]. This behavioral bias, formally described by the prospect theory [28], can be exploited to actively induce consumer participation in DSM programs, even if the aggregated incentive is small on a per capita basis [29]. Moreover, a demand side aggregator could leverage the fact that some grid services, such as peak-shaving, have measurable positive environmental outcomes. These socially desirable impacts can be communicated to consumers and combined with lottery incentives to further encourage PEV owner response [30, 31]. Finally, a DSM service provider could exploit the aggregated information of PEV owner behaviors. This information can provide consumers with a group reference that may translate into additional participation incentives [32, 33]. Co-PI Walker has found this to be effective in promoting sustainable transport behavior in previous work [34, 15].

Figure 5 demonstrates the complexity of predicting whether or not a PEV owner will accept an incentive and participate in DSM programs. The willingness to accept the incentive is a function of (i) the specifics of the incentive offered (type, amount, timing, restrictions), (ii) the vehicle condition and expected vehicle needs (daily tour composition and immediate trip purposes), and (iii) the costs and benefits perceived by the PEV owner. The response is further complicated because of heterogeneity in the population, e.g. financial situation, job and home roles, and a host of attitudes including range anxiety, risk aversion, and environmental stewardship.

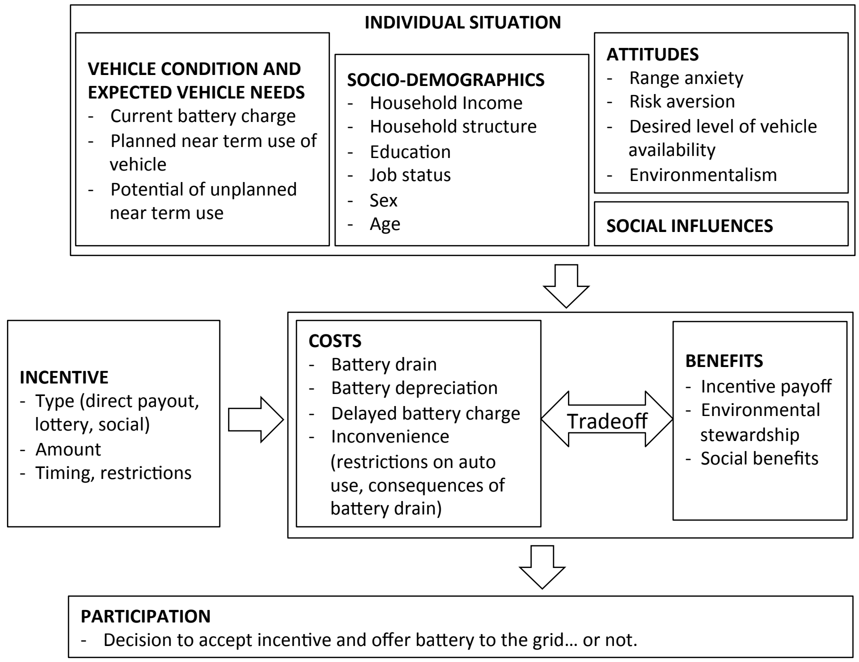

Figure 5: PEV owner decision framework to participate in DSM program.

To develop models that predict participation of PEV owners, we propose discrete choice analysis. Discrete choice behavior models at the individual level are particularly useful for complex underlying behaviors and individual-specific decision contexts. Co-PI Walker in NSF Award 0958110 has integrated approaches in discrete choice analysis, structural equation modeling, and behavioral research similar to Fig 5 for use in policy analysis (see [13, 14, 35, 36]. This previous work demonstrates that demand forecasts can have significant bias if attitudes and lifestyle factors are not considered (see [14]).

To develop the PEV driver behavior model, data must be collected from individuals that are offered specific incentives and asked to accept or decline the incentive offer. Data also needs to be collected on the "individual situation" variables shown in Fig. 5, either via direct survey questions, automatic sensing (e.g., battery state-of-charge), or psychometric survey questions (e.g., for attitudes). The choice contexts on which data are collected can either be based on hypothetical scenarios presented to the subjects (stated preference data, SP) or based on choices that a consumer makes in a real market setting (revealed preference data, RP). In our previous work [37] we quantified traveler willingness to pay in time or money to reduce their greenhouse gas emissions to encourage drivers to shift away from their peak-period auto commute. Various incentives were tested, including direct payout, lottery, and social mechanisms [38]. This previous work uniquely positions us to execute this task, particularly for utilizing survey data for demand forecasts.

Due to the novelty of DSM programs, it is necessary to collect data via Stated Preferences (SP) for this analysis. To ensure SP responses are congruent with behavioral processes that would occur in a real market situation, the SP experiment should enable the respondent to imagine making such a decision in a real context [39]. In the context of DSM and PEV use, this is particularly problematic as it is critical for people to have a personalized understanding of how participating in such programs would impact their travel, their battery state-of-charge, and their budget. This can only be calculated knowing the specifics of an individual's travel patterns. To address this issue, we will use the MyGreenCar smartphone platform developed at Lawrence Berkeley National Laboratory [1], which provides drivers of conventionally-fueled vehicles with personalized information on how PEVs might (or might not) meet their individual travel needs. MyGreen-

Car uses personalized records of travel patterns including travel itineraries and trip-specific drive cycles collected over a period of time (e.g. 3 weeks, 3 months, etc.) to simulate (using V2G-Sim as a back-end) the battery state-of-charge trajectory if the driver used a particular PEV model. For example, MyGreenCar highlights when the electric range is not sufficient to perform the necessary travel. We will combine this with parameters of an incentives program so that our subjects will have a direct understanding of how participation (or not) would impact their specific travel, battery management, and budget (in terms of incentives paid and vehicle costs). The specific tasks are:

Task 2.1: Define Parameters of the Incentives Program. To develop a detailed stated preference survey (Task 2.2), the incentives program and its parameters must be defined. Our initial use case will focus on relieving congestion on the electrical grid, and therefore we will focus on incentive programs that address the timing of charging (e.g., charging early or charging late) and also shifting the place of charging (e.g., from home to work or vice-versa and encouraging park-and-ride by offering parking and charging at transit stations). Further, various payout mechanisms will be tested (direct, lottery, social influences, etc.).

Task 2.2: Design and Conduct Stated Preference Surveys. We will design (year 1) and conduct (year 2) stated preference surveys that present subjects with hypothetical PEV charging and incentive scenarios. We ask whether, under the conditions presented, they would accept the incentive and offer their PEV to the grid. The survey will be interfaced with information from MyGreenCar so that respondents have a personalized understanding of the impact of the incentive program on their personal travel, battery state-of-charge, and budget. We may recruit drivers from our partners' user bases (Automatic, PlugShare, OhmConnect are on Advisory Committee, described in Section 5).

Task 2.3: Estimate Behavioral Models. In year 3 we will use the data collected in Tasks 2.2 to develop behavioral models. The models will predict the probability that a given PEV owner will accept a given incentive (as defined in Task 2.1) at a specific time. These models will be used to evaluate the effectiveness of different forms of the incentives, and assist in the estimation, design and controls efforts of Task 3.

Task 2.4: Incorporate Behavior Models into Simulator. In year 4, the models developed in Task 2.3 will be applied to a simulated population of PEV owners (Task 1) to determine the total available resources under a given incentive program, and subsequently feed into the control and system analysis performed in Task 3. We also seek to determine the optimal mechanism design within the parameters of Task 2.1, with respect to minimizing cost and maximizing resource flexibility.

Expected Outcomes:

- Develop analytic models of PEV owner behavior in the context of DSM to estimate the total expected resources available under a given incentive program.
- Use the consumer behavior models to determine the expected cost required to achieve a certain level of resource availability from the fleet.
- Design recommendations for incentive programs for a PEV fleet.

3.3 Task 3: Network Optimization of the PEV Resource

Task 3.1: Spatio-Temporal Estimation of PEV Storage Resource. This task designs a state estimation algorithm to track the flexible PEV energy storage provisioned from drivers, over space and time, as visualized in Fig. 6. Real-time measurements will be supplied from smart meter and traffic data. The transportation models and traveler behavior from Tasks 1 and 2 will supply the mathematical models.

Reliable state estimation design is challenged by the following properties of our transportation–behavior model: it is nonlinear, large-scale, and uncertain. Ensemble Kalman filters (EnKF) are uniquely positioned for this task. In particular, the EnKF predicts the error statics by propagating an ensemble of state estimates via a Monte Carlo simulation. They key computational advantage is approximating the covariance by the sample covariance of the ensemble members. The EnKF has demonstrated strong success in data assimilation in forecasting [40] and traffic estimation [41], and we adopt similar methods here.

Task 3.2: Analysis of Transportation-Electricity Congestion. Using PEV resource availability and power flow simulation capabilities from Task 1 we will perform an exploratory investigation of transmission network and distribution substation congestion and their correlation with vehicular traffic across space and time (with lags up to 12 hours). Our basic objective will be to quantify the levels of EV penetration (as a function of ownership location) at which traffic and transmission congestion become correlated in ways that suggest the need for either infrastructure upgrades or incentives to alter mobility and charging patterns.

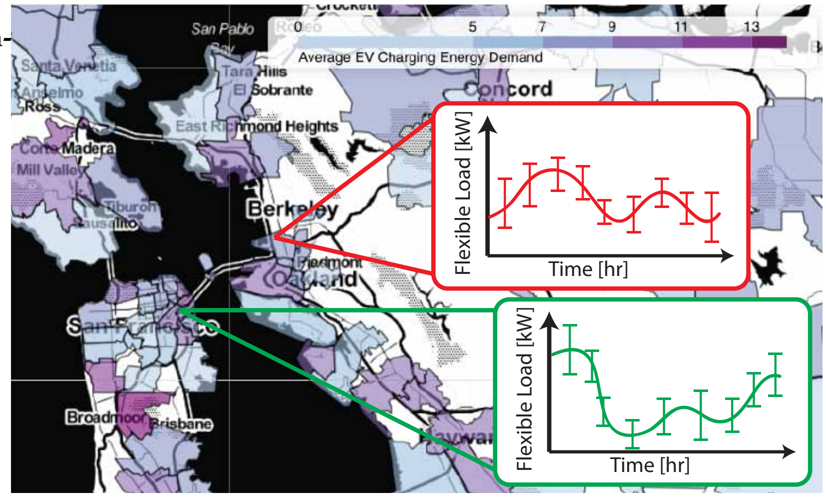

Figure 6: Conceptual interface for spatio-temporal estimation of flexible PEV energy storage provisioned from consumers, via Ensemble Kalman Filtering method. PEV energy storage is aggregated into regions, e.g. sub-LAPs or VATs.

Task 3.3: Network Design to Reduce Congestion. This task seeks to optimally site public EV charging infrastructure to reduce congestion in both the transportation and power system networks while supporting mobility needs. Optimal EVSE siting is critically important for several reasons: First, the costs can be prohibitive, as hardware, installation, and permitting often exceeds $5K for L2 stations and $50K for DC fast charging stations. Second, a lack of convenient charging infrastructure inhibits PEV adoption, creating underutilization. Third, proper siting is impacted by local traffic flow and distribution system loads.

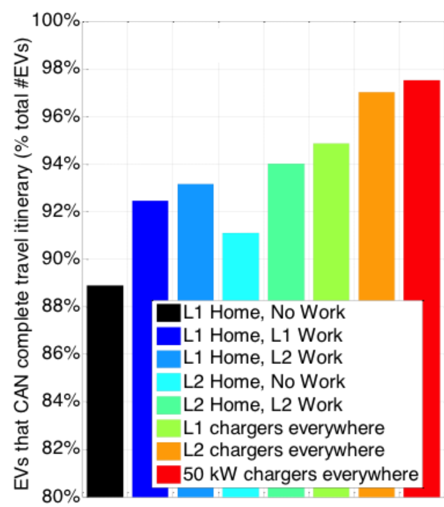

Figure 7: Fraction of U.S. weekday travel needs satisfied by PEVs with various scenarios of charger availability [42].

Recent work has examined EVSE siting to minimize economic cost and total travel times [43, 44], assuming simple models of PEV arrival (e.g. Poisson distributions) and linear charging models. In this work, we relax the existing assumptions by incorporating an integrated PEV charging, traffic flow, and power system circuit model from Tasks 1 and 2. This feature enables us to understand the impact of EVSE placement on spatio-temporal varying traffic flow and grid conditions. In this subtask, we divide the spatial domain into service areas using the aforementioned PG&E distribution network topology data. In addition, we will consider Level 1, Level 2, and 50kW DC fast charging stations, where preceding work focuses on Level 2 or fast charging stations. Our recent work suggests that significant percentages of daily commuting needs can be satisfied by cheaper Level 1 charging stations [42], as shown in Fig. 7.

This problem is non-convex and non-differentiable with respect to the optimization variables, rendering a significant challenge for traditional gradient-based solvers. We will investigate two possible strategies to deal with this challenge. First, if we assume a simplified linear DC power flow model so the problem becomes convex in power flow variables. The problem can then be solved as a mixed integer program. Second, it may be fruitful to leverage recent results on AC power flow problem relaxations that can be solved as semidefinite or second-order cone programs [45]. Alternatively, we can proceed in the spirit of model-based optimization and preserve the full nonconvexity of the problem utilizing Particle Swarm Optimization (PSO) in conjunction with the SmartBay mobility simulator, which sacrifices guaranteed optimality and convergence properties for applicability to non-smooth problems. PSO has shown recent success in similar problems, such as building energy management [46] and hybrid vehicle drivetrain sizing [47].

Task 3.4: Spatio-Temporal Controllability of PEV Charging. This task quantifies how much transportation and electrical demand can be shifted by exploiting PEV driver flexibility. Utilizing the network models in Task 1, and the behavioral models in Task 2, we compute the reachable transportation and power flow sets for given flexibility levels. This task extends our previous work on controllability of demand-side managed loads [48], by considering spatial dynamics and transportation systems. In [48, 49], we find that modest adjustments to load parameters can, in aggregate, yield significant load shaping controllability.

Fundamentally, our approach is founded in reachability analysis, previously developed within the context of hybrid systems [50] and dynamics games [51]. In this previous work, the authors demonstrate that the reachable set is given by the zero sublevel set of a particular time-dependent Hamilton-Jacob-Issacs (HJI) partial differential equation. This HJI equation is analytically derived from a constrained optimal control formulation [52]. Our conjecture is that similar HJI PDEs can be developed within the context of our transportation-electricity networked system.

Practically, this analysis enables answers to the following questions:

- How much load can be shifted by temporally or spatially shifting PEV charging?
- How does this impact transportation demand, traffic flow, and power system congestion?
- How much positive response do we require from incentive mechanisms to provide substantial benefits to the electricity and transportation networks?

3.4 Research Plan Summary

Figure 8 provides a control system-theoretic view of the proposed research plan, represented as a cyber-physical system. Task 1 models the plant - the coupled transportation-electrical transmission circuit networks. Task 2 involves modeling the actuator, represented by human PEV driver behavior. It also considers incentive mechanism design for shifting PEV behavior, represented by the feedback controller. Task 3 involves design (EVSE siting in the plant), system analysis (network congestion, controllability), and state estimation of flexible PEV energy storage provisioned from drivers. Ultimately, we envision the proposed research to generate a suite of modeling, simulation, analysis, estimation, control, and optimization tools for managing urban vehicle-grid systems.

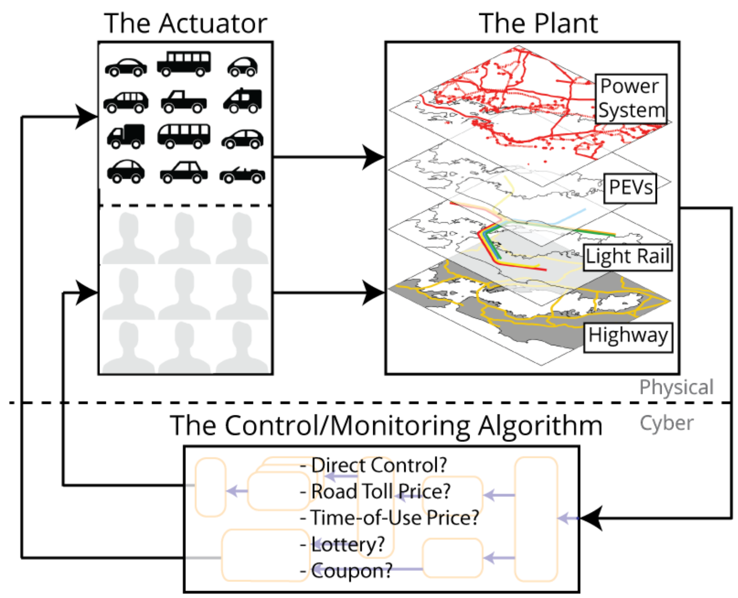

Figure 8: A control systems view of the transportation-power system-human behavior systems. The plant is represented by interconnected transportation-power system networks. The actuator is represented by indirect control via incentive mechanisms to PEV drivers, or direct control of the PEVs themselves.

4 Broader Impacts of the Proposed Work

The contributions described above will provide enabling tools for researchers, practitioners, and policy makers to realize sustainable urban vehicle-grid systems. This project will also advance educational and workforce development in sustainable V2G systems through a series of outreach activities and course development at UC Berkeley. First, we will train three graduate students through the proposed research, providing them with strong interdisciplinary foundations in computational sciences grounded in sustainable energy, power systems, and transportation systems. Each will be co-advised by at least two Co-PIs, and will have opportunities to engage with industry (see Advisory Committee in Section 5) to further their professional development. We fully expect these students to become industry, government, and/or academic leaders in this area. In addition, we plan several outreach and educational development activities.

4.1 Berkeley Energy Resources Collaborative (BERC) & Hackathon

The student researchers participating in this project are deeply involved with campus, regional, and national energy outreach programs. The Berkeley Energy Resources Collaborative (BERC) is the nation's largest student energy organization (over 3500 members and affiliates, with an annual budget of >$150K). Several of the prospective student researchers are officers in BERC.

We will host a "Berkeley Cleanweb Hackathon", themed on Sustainable Urban Vehicle-Grid Systems in 2016 and 2018. The Cleanweb Hackathon is held every spring and draws 30-50 attendees from schools and companies throughout the Bay Area. Each year the hackathon focuses on a theme for which a compelling need exists and ample data is available. The proposed research provides an ideal theme. Past hackathons have led to the creation of innovative companies and nonprofits, which have been incubated at UC Berkeley before becoming successful independent businesses.

The results of this research will be showcased in one of the club's roundtable events, helping engage students from business, policy, law, engineering, and science in the discussion around mobility and energy. The proposed research has been very well-received by the Clean Transportation Working Group, a subgroup of BERC with 50 students from business, policy, and engineering who are passionate about clean transportation. Through engaging with this group, the research team helps to facilitate broader science education and technology transfer to local mobility startups.

4.2 Educational Access to Underrepresented Students

This CyberSEES project will enable educational access to traditionally underrepresented students in several specific ways. First, the PIs combined research groups contain 12 female researchers and 5 students from underrepresented populations (Latino and African-American). This funding enables the PIs to increase this growing community. Second, the PIs will recruit summer undergraduate student researchers via the UC Berkeley Center for STEM Innovation, Leadership, and Diversity. Third, the PIs will serve on career development panels and deliver research plenaries for targeted groups (Hispanic Engineers and Scientists, Society of Hispanic Professional Engineers) to motivate the younger generation to pursue careers in Sustainable Urban Vehicle-Grid Systems.

4.3 Course Development & Integration

The following courses have been recently developed by the co-PIs, and will be educational outlets for disseminating this project's results. These courses represent an emerging curriculum portfolio that teaches various computational tools contextualized within sustainable systems. This Co-PI team, in particular, is uniquely positioned to educate today and tomorrow's leaders in sustainable vehicle-grid systems through their academic program affiliations: Civil Systems, Transportation Engineering, the Energy Resources Group (ERG), and the Energy, Civil Infrastructure, and Climate (ECIC) program.

CE 186: Design of Cyber-Physical Systems (Co-Instructor: Moura, Offered each Fall Semester). This undergraduate project design course explores how PEVs intelligently couple the vehicle and energy infrastructures. Students are introduced to power systems, energy storage, and environmental impacts of electrified transportation. In their project, four-member teams develop a cyber-physical system for vehicle-grid infrastructures, using the E-scooters. In the hardware unit, students learn about sensors, GPS, data acquisition, and signal processing with application to the E-scooter. In the software unit, students develop a cyber infrastructure that allows E-scooters to communicate their charge levels and mobility patterns to a centralized cloud-based webserver. In the final unit, student groups collect data by commuting to their activities across the UC Berkeley campus with the E-scooter. Data analysis provides insights on, for example, charge station location, charging trajectory optimization, grid loads, environmental impact, and battery aging. Students discover, first-hand, the importance of cyber-physical science to the integration of future sustainable urban vehicle-grid systems. This CyberSEES project will significantly enrich this course.

CE 295: Energy Systems and Control (Instructor: Moura, Offered each Spring Semester). CE 295 introduces control system tools for graduate students interested in energy system applications. Applications of interest include batteries, electric vehicles, renewable energy, power systems, and smart buildings/homes. Technical tools include mathematical modeling, parameter identification, state observers, feedback control, and optimization. Students are required to complete a course project involving an energy system of their choice and one or more systems & control tools. Students are encouraged to study sustainable vehicle-grid systems, utilizing tools and frameworks developed in this proposal. This class was inaugurated in 2014, and has seen enrollment double in the 2015 iteration (now at 48 students).

CE 263N: Scalable Spatial Analytics (Instructor: Pozdnukhov, Offered each Fall Semester). This graduate level course introduces tools utilized throughout the project, such as modern methods of data analysis, spatial data handling, and visualization technologies for engineers and data scientists. Theoretical coverage includes a selection of methods from spatial statistics, exploratory data analysis, spatial data mining, discriminative and generative approaches of machine learning. Projects and assignment tasks will be oriented towards the location-based services of sustainable V2G systems, and the domain of "smart cities" in general. The class ran at its full capacity of 50 students at its second offereng in 2015.

ER 254: Electric Power Systems (Instructor: Callaway, Offered each Fall Semester). This popular course teaches students a balance of the engineering principles of the grid up to AC power flow, topics on the economic design and operation of the grid including optimal power flow and integrated resource planning, and emerging issues such as the "smart grid," energy storage, renewables integration and demand response. The course places heavy emphasis on learning through project work. This class will benefit from the integration of the current research results We will lecture on the relationship between EV location and economic dispatch, and we will provide students with detailed case studies to integrate into their research projects.

CE 264: Behavioral Modeling for Engineering, Planning, and Policy Analysis (Instructor: Walker, Offered each Spring Semester). CE 264 teaches the core methods used in Task 3 of this proposal. The course focuses on understanding the human response to engineering, planning, and policy decisions. It covers behavioral theories, survey development, and the use of quantitative methods to analyze human response. A mix of theory and practical tools are covered, with case studies that require exposure to real behavioral data from a variety of applications. A new case study on V2G system consumer response will be developed from the data collected for this project. In the term team project, students will collect their own data, develop a model, and inform an engineering, planning or policy decision related to V2G systems.

5 Evaluation Plan

The project's research task timeline is provided in Fig. 9 and is designed to enable cross-pollination of results. An annual review in January of each year will be conducted by the Co-PIs to assess and evaluate progress. This yearly review will culminate in an annual report submitted to the cognizant NSF Program

Officer. The evaluation criteria for each year are organized as the following list of deliverables, oriented towards providing integrated and multidisciplinary results for enabling sustainable urban vehicle-grid systems to a variety of stakeholders. As the project progresses, the evaluation criteria require increased awareness of the cross-disciplinary sustainability issues.

- **Year 1:** An activity-based mobility model enriched with cellular data. Multiple incentive mechanism designs to procure PEV energy storage flexibility. Preliminary results on transmission circuit models and ensemble Kalman filters for estimating flexible energy storage.
- **Year 2:** A completed transmission circuit model integrated with the activity-based mobility model. Analysis of the dynamical properties of traffic congestion and power system congestion, including their interaction. Preliminary stated preference survey designs.
- **Year 3:** A completely integrated transportation-electricity network model, with preliminary results on uncertainty characterization. Completed state preference survey results, obtained via MyGreenCar, and preliminary behavior models of PEV driver flexibility. Preliminary formulations and results for optimally siting charge stations.
- **Year 4:** A completely integrated PEV driver behavior-transportation-electricity model, with uncertainty. A completed analysis of spatio-temporal controllability of flexible PEV charging.

Advisory Committee: The Co-PI team has assembled an advisory committee consisting of private mobility and infrastructure management companies – OhmConnect, PlugShare, AT&T, and Automatic – and Lawrence Berkeley National Laboratory. Each year, our annual report (prepared for NSF) will be shared with our industry/national lab partners for assessment and feedback. In addition to the partners represented above, the Co-PI team has active collaborations with other regulatory entities (California Energy Commission, California Public Utilities Commission, CalTrans), electric utilities (PG&E and Southern California Edison), and private companies (ChargePoint, Bosch, Samsung) interested in sustainable urban vehicle-grid systems. Results will also be shared with these organizations to generate feedback.

Educational Activities: Products from the proposed research will be tightly integrated within our aforementioned educational curriculum (CE 186, CE 295, CE 263N, CE 264, ER 254). Successful integration and dissemination of these results will be assessed through course evaluations and surveys. Teaching scores and representative student comments will be included in our annual NSF review report. We will also include summarizes of the BERC Hackathon events.

6 Results of Prior NSF Support

PI Moura is Principal Investigator for NSF award number 1408107, "Fast Charging Batteries via Electrochemical Model-based Control," for the period Aug 1, 2014 - July 31, 2017, in the amount of $294,714. The project will maximize the performance of lithium-ion batteries, in applications such as smart phones, electric vehicles, and grid-scale energy storage. Results: **Intellectual Merit:** The key idea is to combine complex mathematical models of battery electrochemistry with recent advancements in control theory. By monitoring the internal electrochemistry via estimation algorithms, one can operate batteries at their performance limits-safely. This involves parameter sensitivity analysis, model-reduction, novel state estimator designs, reference governor algorithms, and experimental tests. **Broader Impacts:** There were 120,000 PEVs sold in the U.S. for 2014. Despite growing sales, "range anxiety" is considered the largest inhibitor of electrified transportation. Significant reduction in charge times, e.g. comparable to filling a gas tank, would eliminate this obstacle and consequently reduce emissions and oil dependence. The PI is working closely with Bosch Research and Technology Center in Palo Alto, California to implement several of these ideas into their business unit products. The project has resulted in publications [53, 54] and a Special Session at the 2015 American Control Conference entitled "The Future of Battery Controls".

Task & Co-PIs	Sub-Task	Description	# of Mo.	Start	End	2016				2017				2018				2019			
						Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
1) Modeling the Coupled Transportation-Power System Networks	1.1	Activity-based Mobility Modeling with Cellular Data	24	1/1/16	12/31/17																
	1.2	Transmission Circuit Modeling	18	7/1/16	12/31/17																
	1.3	Model Integration	30	7/1/16	12/31/18																
	1.4	Uncertainty Characterization	24	1/1/18	12/31/19																
2) Behavioral Modeling of PEV Owners	2.1	Define Parameters of Incentives Program	24	1/1/16	12/31/17																
	2.2	Design and Conduct Stated Preference Surveys	24	10/1/16	9/30/18																
	2.3	Estimate Behavioral Models	30	1/1/17	6/30/19																
	2.4	Incorporate Behavior Models into Simulator	24	1/1/18	12/31/19																
3) Network Analysis and Management	3.1	Spatio-Temporal Estimation of PEV Storage Resource	24	1/1/16	12/31/17																
	3.2	Analysis of Transportation-Electricity Congestion	21	10/1/16	6/30/18																
	3.3	Optimal Charging Station Siting	24	7/1/17	6/30/19																
	3.4	Spatio-Temporal Controlability of PEV Chg	15	10/1/18	12/31/19																
		PI/NSF Annual Review							✔				✔				✔				✔
		NSF Grantees Meeting					✔								✔						
		BERC Hackathon					✔								✔						

Figure 9: Project Management and Subtask Timeline

Co-PI Callaway is Principle Investigator for NSF award number 1239467 "CPS: Synergy: Collaborative Research: Coordinated Resource Management of Cyber-Physical-Social Power Systems," $560,858, for the period Nov. 2012 – Oct 2015, with the first students hired September 2013. This project addresses issues of load management, with a focus on decentralization through game theoretic tools, contract design for central control, and experiments on an electric vehicle testbed. **Intellectual merit:** We have developed several new electric vehicle-to-grid (V2G) coordination schemes, formal results regarding the performance of decentralized coordination in electric power systems relative to centralized approaches, and a "stochastic battery" model that enables power system operators to reliably schedule uncertain demand response resources. **Broader impacts:** Our V2G control tools [55] will be piloted on the Los Angeles Air Force Base EV fleet in Summer 2015 and if successful will be reproduced at a number of bases around the country. The project has resulted in several publications [56, 57, 58, 59, 60, 61, 62, 63, 64, 65] with several other conference papers in review and journal papers in preparation.

Co-PI Pozdnukhov is a beginning investigator who has not received prior NSF support.

Co-PI Walker has been Principal Investigator for NSF awards that were awarded over five years ago.