Cloud Enabled Optimal Charging of Electric Vehicles

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Abstract:

This project implements a demand response (DR) optimization for plug in electric vehicles (PEV) based on time varying electricity price and marginal carbon dioxide emissions signals on the cloud. The optimization solves for the optimal charge trajectory which considers a tradeoff between the cost of electricity and marginal carbon dioxide emissions, energy required to complete trip, and battery health. An electric scooter (ES) outfitted with multiple sensors is used as the PEV to characterize the energy required to complete a trip. An equivalent circuit battery model is used to estimate the state of charge (SOC) of the battery in the PEV, used in the optimization. This work demonstrates how DR charge optimization of PEVs can be performed on the cloud based on the user's desired trip information. A smart charger is actuated from the cloud to perform the time varying optimal charge protocol.

Introduction:

a. Motivation & Background:

The adoption of electric drive vehicles (Hybrid Electric Vehicle: HEV, Plug In Hybrid Electric Vehicle: PHEV, Extended Range Electric Vehicle: EREV, Battery Electric Vehicle: BEV) in the United States is becoming more apparent. In 2010, the total electric drive vehicle (HEV, PHEV, EREV, BEV) sales in the US was 274,555 [1], where only 345 of those where EREV's (326), and BEV's (19). In 2012 total electric drive vehicle (HEV, PHEV, EREV, BEV) sales in the was US 487,480 [1], where 52,835 were Plug In Electric Vehicles (PHEV's, EREV's, BEV's). The sales breakdown for 2010/2012 is shown in Table I-II.

TABLE I. ELECTRIC VEHICLE SALES IN THE US (2010) [1]

2010				
Month	Hybrids (HEV's)	Extended Range (EREV's)	Battery (BEV's)	Total
January	17,157	--	--	17,157
February	16,530	--	--	16,530
March	23,274	--	--	23,274
April	23,654	--	--	23,654
May	28,202	--	--	28,202
June	21,679	--	--	21,679
July	23,841	--	--	23,841
August	24,002	--	--	24,002
September	22,193	--	--	22,193
October	24,228	--	--	24,228
November	20,858	--	--	20,858
December	28,592	326	19	28,937
Total	274,210	326	19	274,555
	Total Vehicle Sales YTD			11,588,783
	Electric Drive Market Share			2.37%

TABLE II. ELECTRIC VEHICLE SALES IN THE US (2012) [1]

2012				
Month	Hybrids (HEV's)	Plug-In Hybrid (PHEV's) incl. Extended Range (EREV's)	Battery (BEV's)	Total
January	21,778	603	824	23,205
February	36,222	1,023	639	37,884
March	48,206	3,200	961	52,367
April	39,901	3,116	775	43,792
May	37,184	2,766	612	40,562
June	34,558	2,455	863	37,876
July	31,610	2,537	479	34,626
August	38,369	3,878	837	43,084
September	34,835	4,503	1,306	40,644
October	33,290	4,994	2,040	40,324
November	35,002	4,544	2,211	41,757
December	43,690	4,965	2,704	51,359
Total	434,645	All Plug In's:	52,835	487,480
	Total Vehicle Sales YTD			14,439,684
	Electric Drive Market Share			3.38%

DR is a good opportunity for optimally charging PEVs based on cost of electricity, marginal carbon dioxide emissions, energy required to complete trip, and battery health. The electric utility, environment, and end consumer benefits from this, as there will be less demand during peak hours, reduced emissions, and the life of the battery in PEVs extended over time when compared to conventional charging. Extending the battery life in a PEV is very important as it is the costliest component.

b. Relevant Literature:

This work takes the cost of electricity for charging PEVs from PG&E [2], the marginal carbon dioxide emissions from WattTime [3], uses a DR optimization formulation based on the work in [4], estimates average energy consumption based on road grade and distance, and considers lithium ion battery health based on the work in [5]. That is, the battery should be stored at low state of charge (SOC) levels to avoid degradation, and hence the battery should only be charged enough to complete the trip. It should be noted that there is much excitement in this field amongst EV manufacturers, technology companies, labs, and electric utilities [6-15].

c. Focus of this Study:

The focus of this study is to demonstrate the cost/emissions/peak energy benefits to the user and grid by developing a cyber physical system that optimally charges PEVs via a cloud based optimization solver, an ES, and a smart charger.

Technical Description:

The objective of this project is to develop a cyber physical system which takes desired trip information from a user through a web interface (which obtains trip distance and elevation changes from the Google Maps Directions and Elevations APIs [16]) and converts that to an estimate of needed energy from the PEV (calculated from an average energy model derived from data) to complete the desired trip. That information is used to optimize the EV charging strategy based on electricity time of use cost and marginal carbon dioxide emissions. The PEV has hardware (Cycle Analyst/Arduino) to sense and record (SD card) time, velocity, distance, voltage, current, power, and acceleration. The data is transmitted wirelessly to the charger (XBee) to determine an energy model and battery state of charge. The data is then used for optimizing the charge strategy over the cloud, actuated via a charger relay.

a. Average Energy Model

The average energy model is determined from data obtained from multiple trips taken as a function of road grade is as follows:

$$E_{coeff} = 1.1197\theta^2 + 9.8634\theta + 37.598$$

whose units are in Wh/mi with θ as the road grade in degrees calculated from the elevation change and distance traveled. The trip data points (determined from energy consumed in Wh divided by trip distance in mi for a specific road grade in degrees) and polynomial fit (average energy model) is shown in Fig 1.

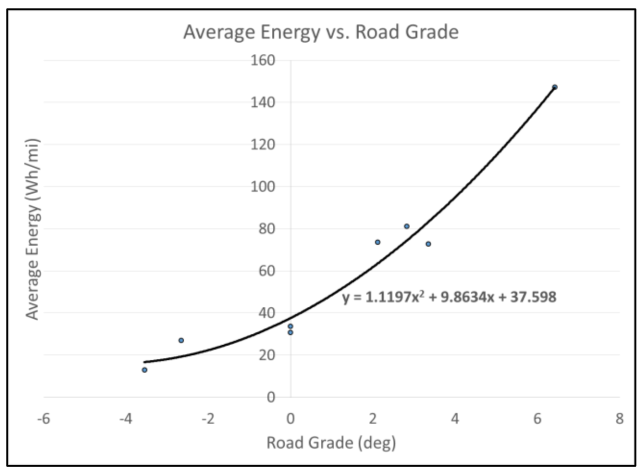

Figure 1: Average Energy vs. Road Grade

The processed trip data is shown in the appendix.

b. Optimization Formulation

The optimization formulation for optimally charging the PEV is as follows:

$$\min_{s_k} \sum_{k=0}^{N-1} \beta c_k (RI^2 + V_{OCV} I)\Delta t s_k$$
$$+\alpha(1-\beta) e_k (RI^2 + V_{OCV} I)\Delta t s_k$$

Subject to

$$x_{k+1} = x_k + \frac{I}{Q_{batt}} \Delta t s_k \; for\ k = 0, \dots, N-1$$
$$x_k \geq SOC_{min} \; for\ k = 1, \dots, N-1$$
$$x_0 = SOC_0$$
$$x_N = SOC_f$$
$$s_k = \{0,1\} for\ k = 0, \dots, N-1$$

The objective function minimizes the overall cost of electricity ($) based on the cost of electricity ($/kWh) c_k, the marginal emissions ($lbCO_2$/kWh) e_k, the charging power (kW) $RI^2 + V_{OCV} I$, tradeoff parameter β, emissions cost factor ($/$lbCO_2$) α (assumed to be 1), with the charging state (0=OFF,1=ON) s_k as the decision variable. The first constraint is the battery SOC model dynamics, where Δt is the time difference between time step k+1 and k. The second constraint ensures that the battery SOC stays above its minimum SOC. The third constraint defines the initial SOC (calculated from the at rest voltage of the PEV before charging). The fourth constraint is the terminal constraint which defines the terminal SOC that is required based on the energy estimate from desired trip parameters. The fifth constraint defines the decision variables (charger state) as binary.

The initial SOC is found from looking up the corresponding SOC from the PEV rest voltage in the Open Circuit Voltage vs. SOC (determined as the average curve from experimental C/10 CCCV cycling) map of the battery shown in Fig. 2.

The terminal SOC is calculated as follows

$$SOC_f = SOC_0 + \frac{E_{coeff} d_{trip}}{E_{batt}}$$

Where E_{coeff} (Wh/mi) calculated from the road grade θ (deg), and the trip distance d_{trip} (mi).

Some of the parameters used for this problem for the ES are as shown in Table III.

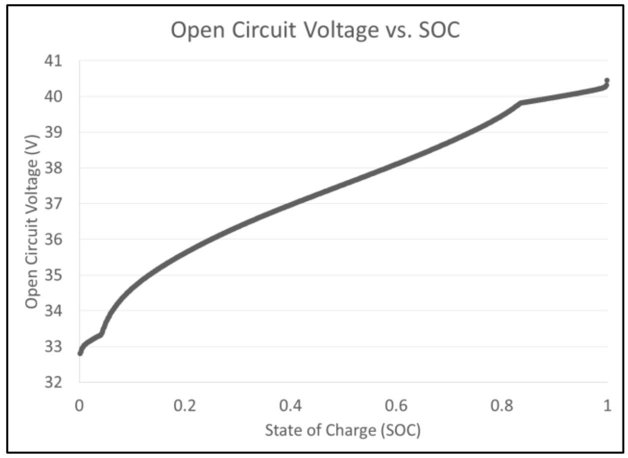

Figure 2: Open Circuit Voltage vs. SOC

The rest come from real time electricity price and emissions data, and user inputs.

Table III. ES Parameters

Parameters				
Internal Resistance R (Ohm)	Charge Current I (A)	Open Circuit Voltage V_{OCV} (V)	Battery Capacity Q_{bat} (Ah)	Energy Capacity E_{batt} (Wh)
0.13	1.67	37.534	14	566.34

c. Cloud Implementation

The diagram in Fig. 3 shows the implementation over the cloud.

The user web interface shown in Fig. 4 takes in the current state of the PEV (calculated by the cloud app), desired trip information for the user, extracts google maps API data to produce a trip route with road grade and sends it to the cloud app.

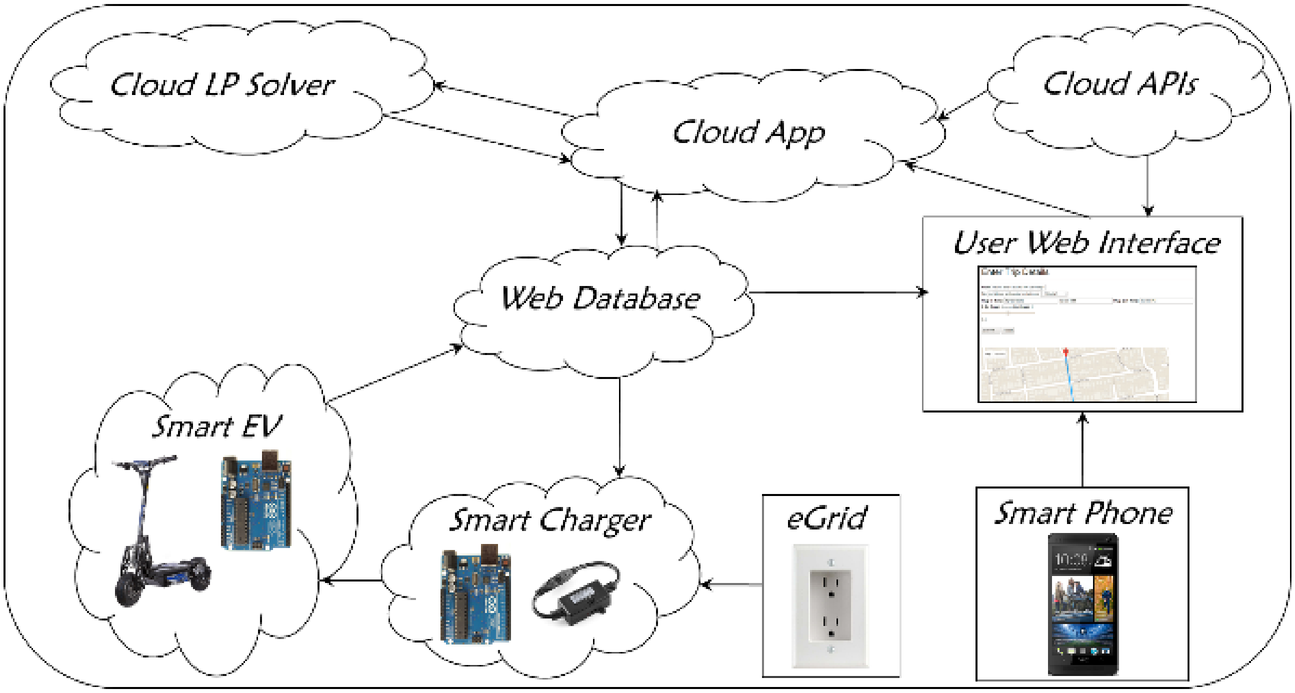

Figure 3: Cloud Optimization System

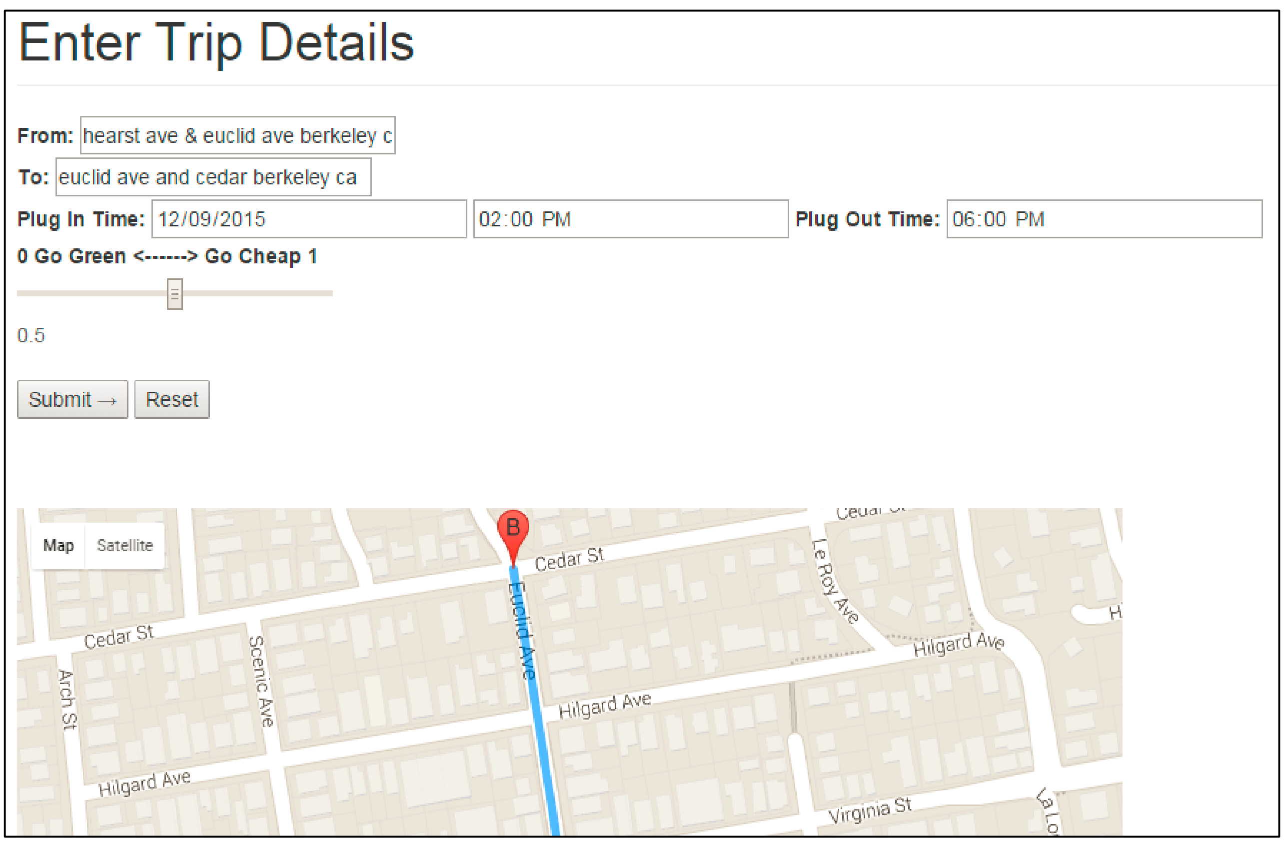

Figure 4: User Web Interface

The cloud app then processes that data to find an energy estimate along with the marginal emissions data and cost of electricity to form the optimization problem and sends it to the cloud mixed integer linear program (MILP) solver. The cloud MILP solver then sends the optimal charge trajectory back to the cloud app. The cloud app then sends the optimal charge trajectory to the web database. The smart charger then obtains that optimal charge trajectory and actuates the charger accordingly.

d. Bill of Materials

The bill of materials is shown in Table IV.

Table IV. Bill of Materials

1	1kW Electric Scooter	CE186 Supplied
2	Cycle Analyst	
3	DC/DC Converter	
4	Arduino Mini	
5	SD Card Shield	
6	Accelerometer	
7	XBee (2)	
8	Arduino UNO	
9	PowerSwitch Tail Relay	
10	Power Supply	

e. List of Software Code and Functions

1. ES Datalogger: Logs data in SD card from trips for characterizing energy model

2. User Web Interface: Takes in user trip parameters, rest voltage of ES, and calculates distances, road grades, and initial SOC for the charge optimization. Also displays solution.

3. Optimization: Takes in data from user trip parameters and current SOC of ES and determines optimal charge schedule.

4. Actuation: Receives charge signal and actuates smart charger.

Discussion:

The Optimal Charge and SOC Trajectory for a sample trip is shown in Fig. 5. The trip parameters are as followed: Desired Trip Time at 10AM, Trip Distance 2.5 Miles, Trip Road Grade 1.9^o, Current SOC 0.5, Tradeoff parameter 0.5. This trip is different than Fig. 4.

The optimization starts at 6:00AM at which the charger starts charging the battery. The end of the optimization occurs at the desired trip start time at 10:00AM. The yellow bars in the top subplot of Fig. 5 (within the optimization time frame) indicate when the charger is ON, and the blue bars indicate when the charger is OFF. The bottom subplot of Fig. 5 shows the SOC trajectory of the battery as it is charged. Note that when the charger is OFF (as seen by the blue bars in the top subplot of Fig. 5), the SOC stays the same because the battery is not being charged during this time. The final SOC that results from charging the battery is an SOC of 0.798. The solution can be explained as follows: the battery is charged when combined cost is lowest, only as needed to charge the battery to its required SOC to complete the trip. The total cost of charging is $0.0831.

This work shows how DR optimization can be implemented over the cloud for a PEV subject to user trip requirements, cost of electricity, emissions, etc. If applied to an aggregation of PEV's, then it will positively impact the electric grid due to loads being shifted out of peak times (based on cost of electricity). This is especially important as the number of PEV's that connect to the grid continue to grow over time, as seen by the growth in sales of EV's, shown previously. There will also be a considerate amount of cost savings to all of the end consumers as a whole. This work provides a framework for cloud based optimization of PEVs which can be expanded to include other objectives and loads/energy sources. The innovations of this work involve the full integration of this cloud based system.

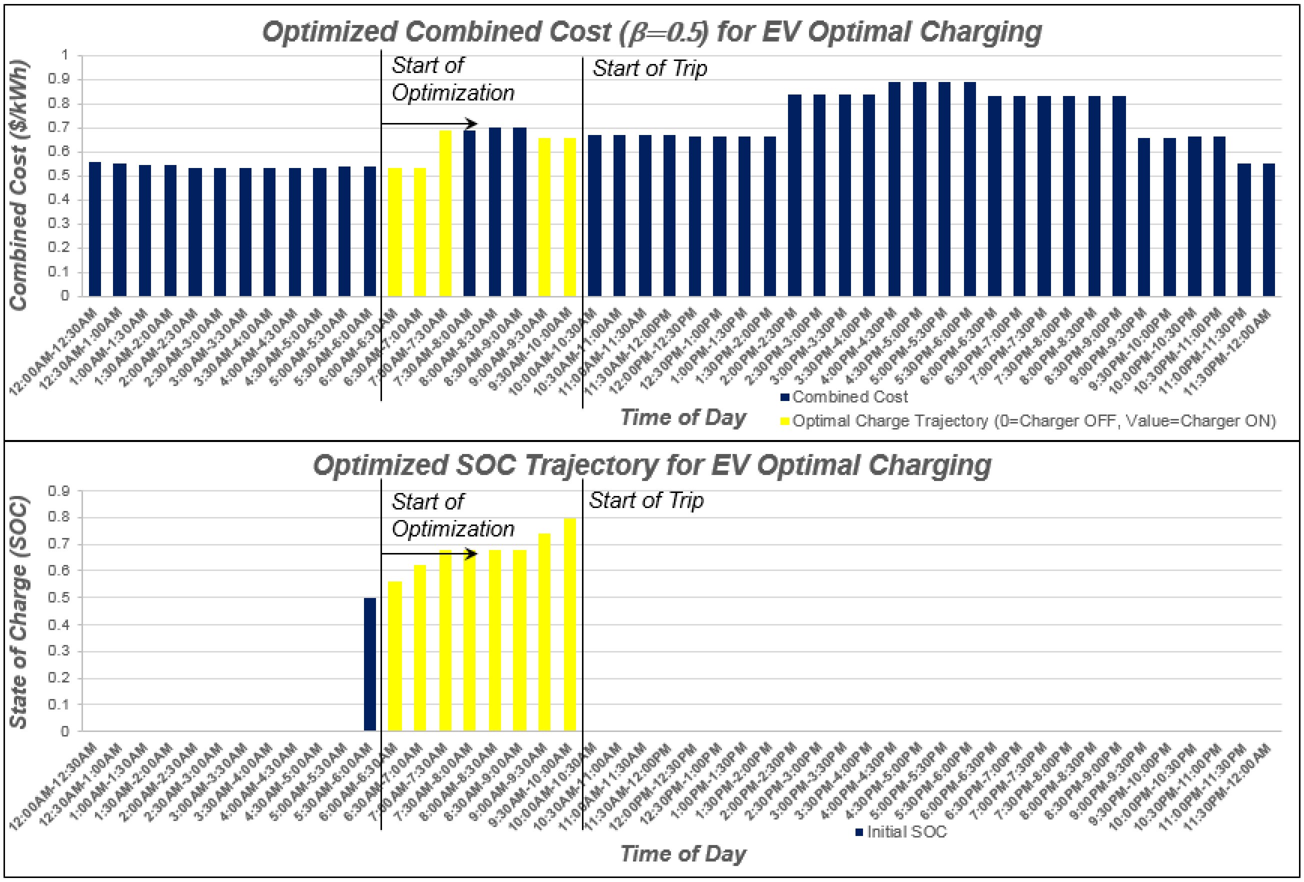

Figure 5: Optimized Combined Cost and Charge Trajectory (Top) and SOC Trajectory (Bottom)

Summary:

This work implements a demand response optimization problem for cloud enabled optimal charging of electric vehicles. The optimized charge and SOC trajectory are cost of electricity, emissions, trip length, and battery health conscious which are important to the electric utility and end consumer. Potential benefits of this cyber physical system are illustrated.

References:

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[3] WattTime API. Available Online: https://api.watttime.org/

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[16] Google MAPS APIs. Available Online: https://developers.google.com/maps/?hl=en

Appendix:

Table V. Processed Data from Trips

Processed Data from Trips						
Trip	Elevation Chg (ft)	Distance (mi)	Distance (ft)	Grade (deg)	Energy (Wh)	Avg Energy (Wh/mi)
0	102	0.331	1747.68	3.347556946	24.12	72.87009063
1	39	0.2	1056	2.117592167	14.749	73.745
2	-98	0.3	1584	-3.548879111	3.904	13.01333333
3	0	0.1	528	0	3.068	30.68
4	0	0.1	528	0	3.367	33.67
5	52	0.2	1056	2.823956176	16.217	81.085
6	-49	0.2	1056	-2.66091492	5.394	26.97
7	59	0.1	528	6.419022623	14.724	147.24

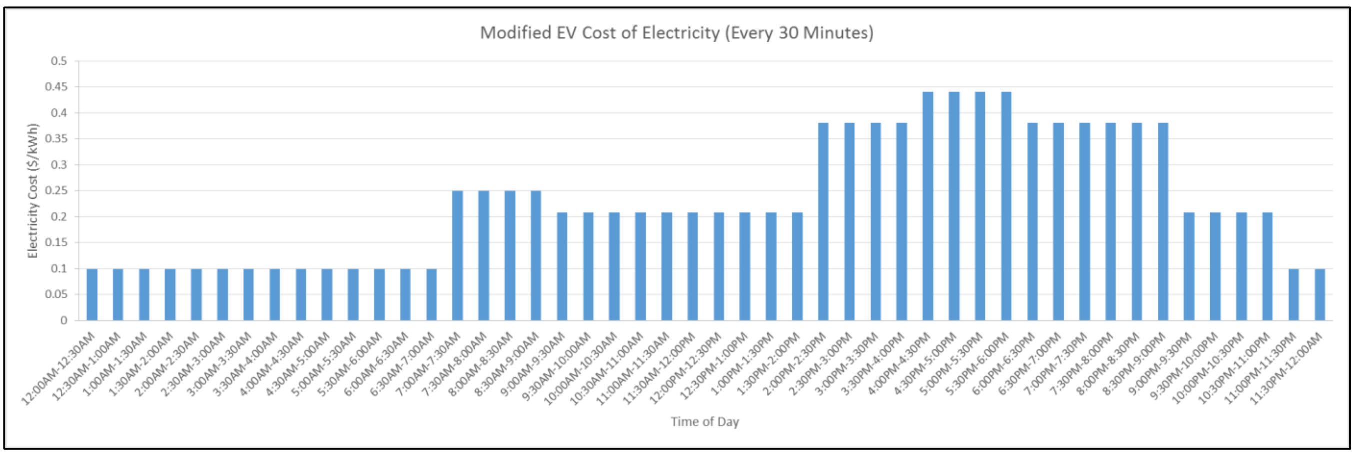

Figure 6: Modified EV Cost Schedule (PG&E)

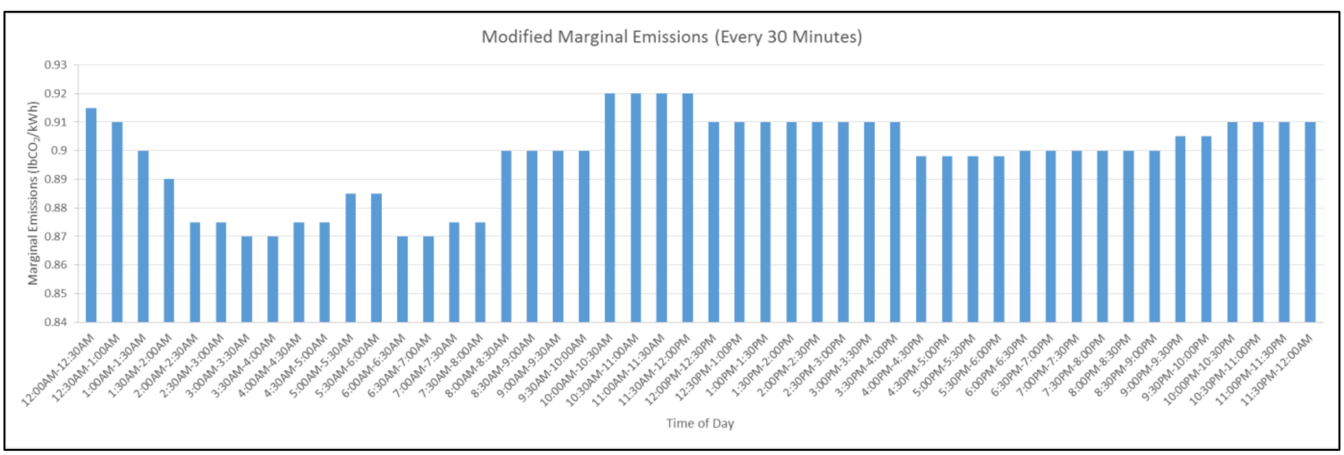

Figure 7: Modified Marginal Emissions (Wattime)

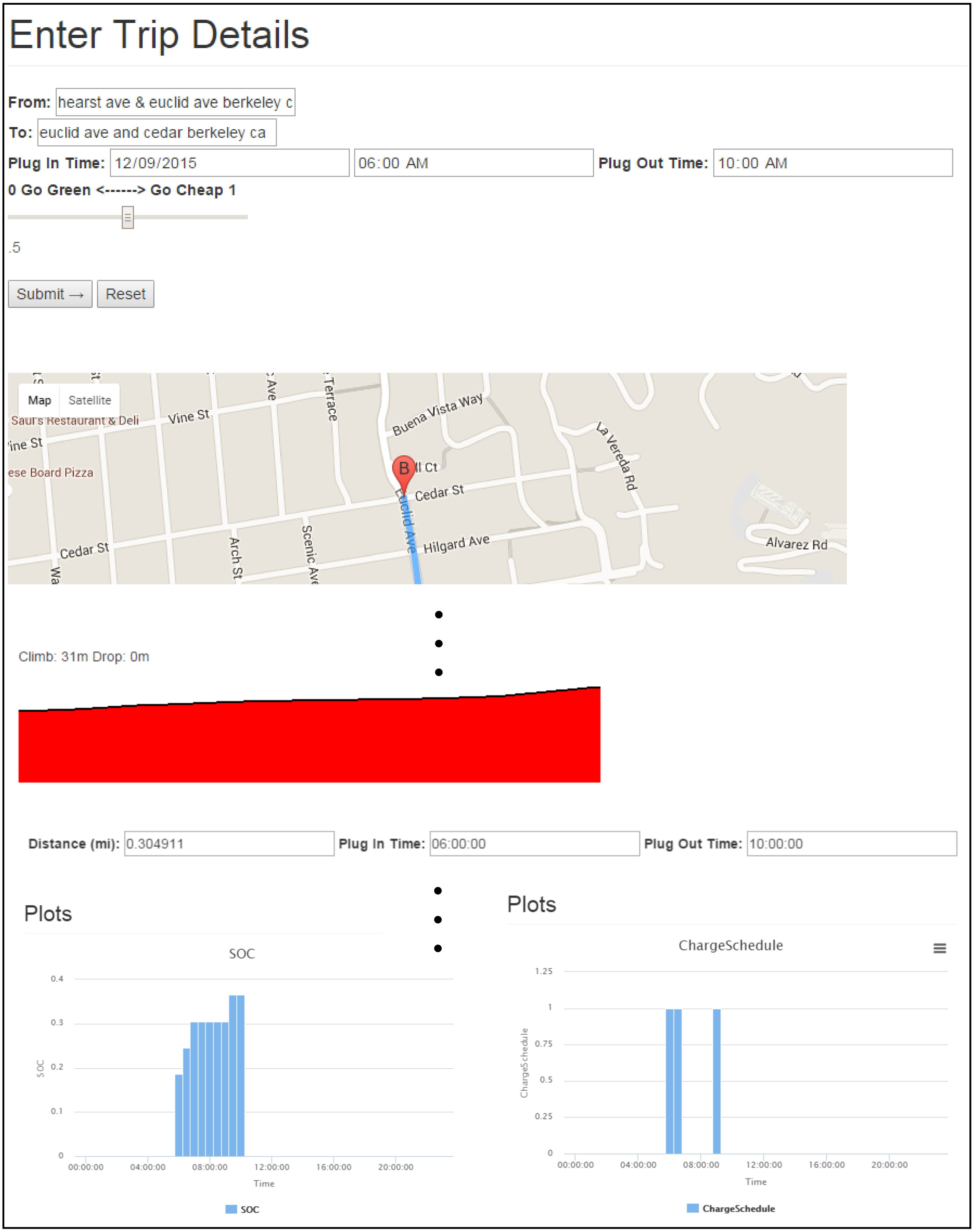

Figure 8: Overview of Web Interface