A FRAMEWORK FOR QUANTITATIVE ANALYSIS OF GOVERNMENT POLICY INFLUENCE ON ELECTRIC VEHICLE MARKET

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Abstract

There is increased government intervention worldwide towards supporting growth of the global Electric Vehicle (EV) market motivated by public interest in greenhouse gas emission reduction and energy security. Previous studies have shown a positive relationship between government investment and the growth of EV market share within the overall vehicle market. This paper describes a quantitative framework for analyzing the effect of EV-related government policies on emissions reduction that includes modeling decision making of the manufacturer, charging service operator and consumer.. Two interesting findings from applying this framework to specific urban use scenarios are reported. First, if the budget for the relevant government subsidies is increased, the focus should shift from direct support of battery EVs to building public infrastructure such as charging stations; second, government policies that affect the design of both charging services and EVs would allow the government more effective use of its investments.

Keywords: Decision making, Optimisation, Government policy, Electric vehicle

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1 INTRODUCTION

The global electric vehicle market is growing in order to reduce greenhouse gas emissions and increase energy security. A recent review of major EV markets in the US, EU and East Asia showed that government public policies have been playing a major role in fostering this market growth (Mock and Yang, 2014). Such policies include (a) incentives for consumers (e.g., purchase bonus, reduced tax, and electricity cost discount), (b) infrastructure (e.g., charging station) development, and (c) investment in research and development. The above study also revealed how different emphasis in policy has led to different market shape. For instance, Norway has now the highest percentage of Battery EV (BEV) market share due to its high BEV incentives (e.g., low electricity cost and low taxes) and high fuel cost; while the Netherlands have the fastest-growing market in Plug-in Hybrid Electric Vehicles (PHEV) due to their policy emphasis. While current market data show positive correlation between government investments and the market share or growth rate for several countries (Mock and Yang, 2014), it is still unclear how government policies should be configured to induce an EV market growth consistent with government desires and attendant roadmaps.

This paper is an initial attempt to address this question quantitatively by modeling the EV market as a game, with three stakeholders playing to reach equilibrium: Government, manufacturer and infrastructure (charging station) operator. For the government, we consider four types of public policies related to EV as realized in the US: (a) Recharging cost discount, (b) one-time EV purchase discount for consumers, (c) charging station subsidy, and (d) manufacturer subsidy for EV production. For the manufacturer, we focus on profit-maximizing decisions related to battery and powertrain design. For the charging station operator, we consider station location selection and charging service fee as value-maximizing decision variables, where value may include public interest.

The resultant game equilibrium, under typical simplifying assumptions, reveals how the government budget can be optimally allocated to the manufacturer, the consumer and the charging station. Due to lack of a “standard” widely-adopted EV business model, we examine and compare three game scenarios for EV use in an urban setting: (a) All three stakeholders make decisions together to maximize a weighted sum of emission reduction and profit, (b) the manufacturer seeks maximal profit, while the government owns the charging service and aims at emission reduction, (c) all three stakeholders have their own objectives. Parametric studies explore how different budget levels affect emission reduction and profits.

The remainder of the paper is structured as follows. Section 2 introduces the proposed framework and elaborates on modeling details and assumptions. Section 3 presents the game equilibrium results for the three scenarios and various parameter settings, and examines the causes for the differences among scenarios. Section 4 provides conclusions and suggestions for future work.

2 PROPOSED FRAMEWORK

We consider three stakeholders in a game-theoretic decision framework. The government determines public policies about subsidies; the EV manufacturer determines vehicle powertrain and battery designs for its BEV and PHEV products, and the charging station (CS) operator determines number and locations of charging stations as well as charging fee. The market shares of EV, PHEV and conventional vehicles are then determined by vehicle and charging service design attributes. Fig. 1 summarizes the interactions among stakeholders and their decisions. Table 1 lists input decision variables, parameters, and output responses for each model. In order to investigate policy differences across various urban/suburban environments, we use three “city type” parameters, namely, drive cycle, candidate charging stations locations, and market size. The drive cycle and station locations directly affect manufacturer and charging station operator decisions, respectively, while market size affects the profit as predicted by a marketing model.

We assume that equilibrium for all stakeholders will be reached for the given models and parameters. We define the public policy at equilibrium as the optimal policy. Due to lack of widely-accepted EV business models, we examine three decision-making scenarios that could result in different equilibrium points (i) *All-In-One Scenario*: The government, manufacturer, and charging station operator share a common interest in optimizing a weighted sum of emission reduction and profit from vehicle sales and from charging service; (ii) *Two-stakeholder Scenario*: The manufacturer only considers its own profit from vehicle sales, while the government aims to minimize the emission within its budget limit, taking charging service expense or profit into account; this is the case where charging stations are government-owned operations; *(iii) Three-stakeholder Scenario*: All players reach equilibrium using their own objectives. Fig. 2 summarizes the problem formulations for these three scenarios. Note that we enforce government decisions so that they result in non-negative profits for both manufacturer and station operator across all scenarios.

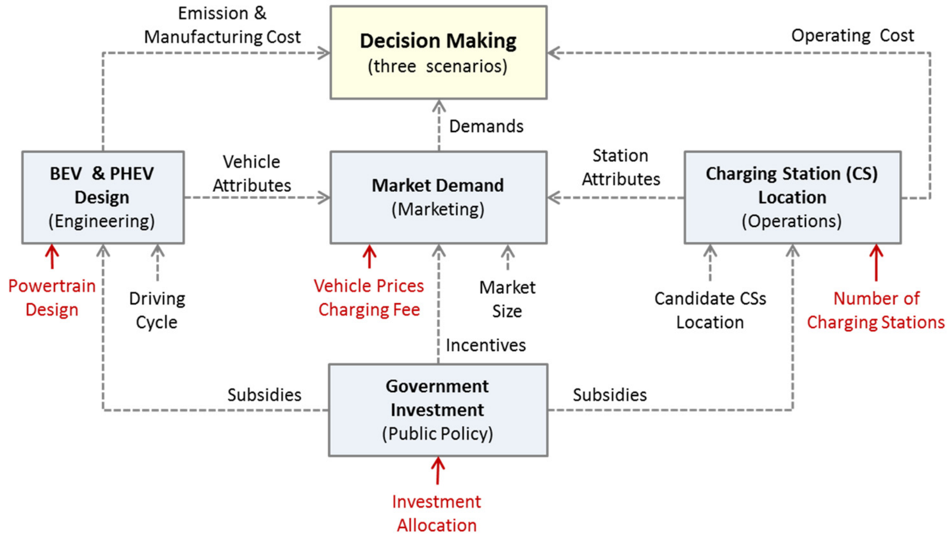


Figure 1. Multidisciplinary decision making framework for the EV market

Table 1. Input decision variables, parameters, and output responses for each model

	Public policy	Engineering (BEV and PHEV)	Operations	Marketing
Decision variable	EV and charging station subsidies, electricity price cut and tax cut	Number of battery cells, gear ratio	Number of charging stations	Vehicle price Energy charging fee
Input		Drive cycle	Candidate charging station locations	Market size, Outputs from the powertrain design and charging station models
Output	Public policy cost	Vehicle range, speed, acceleration, energy consumption, PHEV emission, and manufacturing cost	Average distance to the closest station Operating cost	EV demand Charging station demand

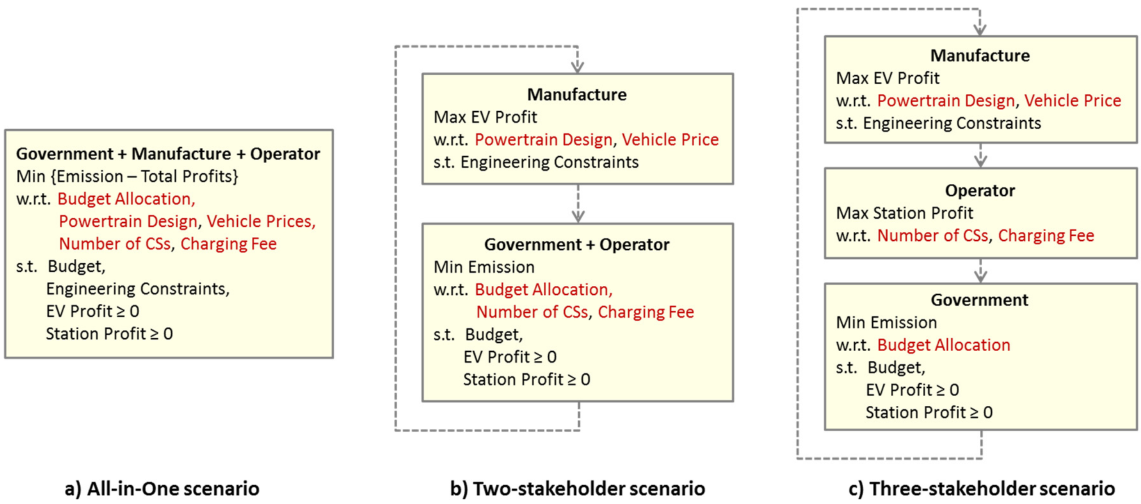


Figure 2. Three business scenarios for optimal decision making

2.1 Public Policy Model

We consider four types of public policy currently available in the U.S. as decision variables for the government. Table 2 lists notations, definitions and bounds for these variables.

Table 2. Public policy decision variables

Decision variable	Definition	Lower bound	Upper bound
1. EV subsidy	Subsidy per kWh of battery capacity for the manufacturer	\$0	\$600
2. CS subsidy	Percentage of subsidized installation and maintenance costs for the charging station operator	0%	100%
3. Electricity price cut	Percentage of cut of electricity price for station operator	0%	100%
4. One-time tax cut	Percentage of cut of registration fee for EV user	0%	100%

Based on these decision variables, the total subsidies on EV, CS and electricity, as well as the one-time tax cut can be calculated as follows:

$$Total\ EV\ subsidy = EV\ subsidy \times (BEV\ battery\ capacity\ \times\ BEV\ demand + PHEV\ battery\ capacity\ \times\ PHEV\ demand) \quad (1)$$

$$Total\ CS\ subsidy\ =\ Number\ of\ CSs\ \times\ CS\ subsidy\ \times (Installation\ cost + Maintenance\ cost) \quad (2)$$

$$Electricity\ subsidy\ = Electricity\ price\ \times\ Electricity\ price\ cut\ \ \times (BEV\ battery\ capacity\ \times BEV\ charging\ demand + PHEV\ battery\ capacity \times\ PHEV\ charging\ demand) \quad (3)$$

$$Total\ one\ time\ tax\ cut\ =\ Tax\ cut \times\ (BEV\ demand + PHEV\ demand) \quad (4)$$

The station maintenance cost in Eq. (2) and the electricity subsidy in Eq. (3) are calculated considering net present value for 10 years with 10% discount rate, assuming that every EV has a 10-year life span.

2.2 Engineering Model

We model one manufacturer that designs and sells a BEV, a PHEV and a conventional gasoline vehicle. The three vehicle simulation models are built using the AMESim software (AMESim, 2014) and following typical specifications for the Nissan Leaf, Toyota Prius Plug-in and Volkswagen Jetta vehicles, respectively, as representative examples. We use battery specifications from the Nissan Leaf for both the BEV and the PHEV. All vehicle component specifications are listed in Table 3. Note that the simulation models are meant to approximate the aforementioned representative vehicles rather than to provide high-fidelity models for them.

Each vehicle model takes a drive cycle as input and uses a PID controller as the driver to follow the cycle. The control gains are fixed for all vehicle simulations. CO2 emissions are derived from simulations of the PHEV and the gasoline vehicle. The PHEV energy management control strategy is tuned to maximize electric-only range for the given drive cycle (rather than for sustaining the state of charge). The initial state of charge is set at 80% which reflects the state of the battery after visiting a fast-charging station. Powertrain control involves an ICE controller, an electric motor controller and a hybrid strategy controller. The hybrid strategy controller regulates energy flows by setting conditions to turn the engine on/off based on State of Charge (SOC), power request or wheel rotary velocity values.

We consider three design variables: (1) the number of cells in series in one battery branch, (2) the number of branches in parallel, and (3) the final drive gear ratio, as listed in Table 4. For a given set of input variable values, the simulation outputs values for the emissions, range, battery/fuel consumption, top speed, 0-60mph acceleration, and vehicle manufacturing cost. Among these outputs, range and battery/fuel consumption are input parameters for the market demand model. Top speed and acceleration serve as engineering constraints: A feasible design should have a top speed greater than 70 mph, and 0-60 acceleration less than 30 seconds. Emission reduction is used as the government objective. Vehicle costs, including battery cost and fixed vehicle cost, are calculated following Kang et al. (2015).

Table 3. Vehicle component specifications

	BEV	PHEV	Gasoline
Vehicle weight	1696kg	1380kg	1307kg
Tire radius	315.95mm	315.95mm	300.3mm
Coefficient of drag	0.29	0.29	0.3
Frontal area	2.27m^2	2.27m^2	2.10 m^2
Engine size	-	1.8L	2.0L
Engine max. torque	-	142.5Nm @ 4000rpm	169.5Nm @ 4000 rpm
Engine max. speed	-	4500rpm	6500-6900rpm
Engine max. power	-	73kW @ 5200rpm	85.8kW @ 5200 rpm
Fuel tank capacity	-	40.1l	54.9l
Motor(s) type	PMSM	PMSM	-
Motor(s) max. torque	280Nm	200Nm for both	-
Motor(s) max. speed	10390rpm	12000rpm for both	-
Motor(s) max. power	80kW	60 kW and 42kW	-
Battery cell capacity	33.1Ah/#cells	33.1Ah/#cells	-
Battery package capacity (before optimization)	24kWh battery	12kWh	-

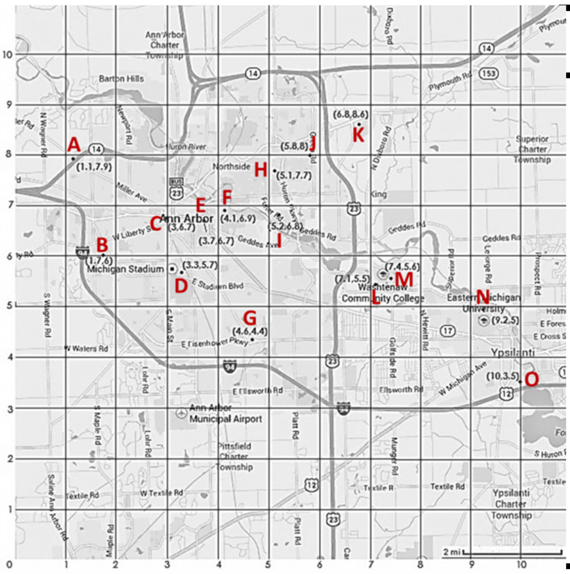
Table 4. Engineering design variables

Design variable	Lower bound	Upper bound
1. Number of cells in series in one branch of BEV	80	200
2. Number of branches in parallel of BEV	1	4
3. Gear ratio of BEV	2	12
4. Number of cells in series in one branch of PHEV	1	50
5. Number of branches in parallel of BEV	1	4
6. Gear ratio of PHEV	5	7

2.3 Operations Model

Given a target city, the operations model takes as input the number of charging stations and picks from a candidate set of charging stations the optimal ones. Here we consider Direct Current (DC) fast-charging stations that can recharge a 24 kWh battery to 80% capacity within 30 minutes. We adopted the p-median model (Tansel et al., 1983) to determine the optimal set of stations: In choosing p stations, the optimal locations minimize the average distance between any EV on the map and its closest station. The model then calculates the average distance to the closest station from any EV user, assuming that users are uniformly distributed in the city. This distance is used in the market demand model. The charging station operating cost is also calculated based on the number of charging stations, considering installment, maintenance, and electricity costs (Kang et al., 2015).

The example city (Ann Arbor, Michigan, USA; 11 miles by 11 miles) has 15 candidate charging station locations, selected among its existing public parking lots, as seen in Fig. 3. The optimal locations are pre-optimized for p from 1 to 15, and the corresponding average distances are recorded. For example, if we plan to build five charging stations, locations A, B, G, K, and N in the figure will be chosen.



# of CS	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1									•						
2				•										•	
3				•							•			•	
4	•						•				•			•	
5	•	•					•				•			•	
6	•	•					•	•			•			•	
7	•	•					•	•			•	•		•	
8	•	•					•	•			•	•		•	•
9	•	•			•		•	•			•	•		•	•
10	•	•		•		•	•	•			•	•		•	•
11	•	•	•	•			•	•	•		•	•		•	•
12	•	•	•	•		•	•	•	•		•	•		•	•
13	•	•	•	•		•	•	•	•	•	•	•		•	•
14	•	•	•	•		•	•	•	•	•	•	•	•	•	•
15	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

Figure 3. Optimal charging station locations using candidates (A to O)

2.4 Marketing Model

Three pricing variables are of interest in modeling the market demand. These are BEV and PHEV retail prices and the charging fee. To estimate market demand, we build a linear utility model with six attributes: (1) Vehicle type (BEV, PHEV or Gasoline), (2) vehicle price taking EV subsidy into account, (3) registration fee, (4) vehicle range, (5) fuel cost to fully refuel (or recharge) the vehicle, and (6) average distance to the station. Besides vehicle type, each of the other five attributes is assigned five levels, as summarized in Table 5.

Table 5. Attributes levels and their part-worths

Attributes	Unit	Level (part-worth) 1	2	3	4	5	Importance
Vehicle type		BEV (-0.50)	PHEV (0)	Gasoline (0.50)			7.8%
Vehicle price	US$	15k (1.94)	25k (0.97)	35k (0)	45k (-0.97)	55k (-1.93)	30.0%
Registration	US$	0 (0.13)	40 (-0.13)				2.0%
Vehicle range	miles	70 (-1)	150 (-0.5)	250 (0)	350 (0.5)	450 (1)	15.5%
Fuel cost	US$	0 (1.13)	15 (0.57)	30 (0)	45 (-0.57)	60 (-1.13)	17.5%
Avg. distance to the station	miles	0.5 (-1.75)	3 (-0.88)	5 (0)	7 (0.88)	10 (1.75)	27.2%

The linear utility model assumes additive utilities from all attribute levels. Assuming a homogeneous population, the part-worth values, i.e., weights, on these levels are approximated as follows. Denote "attribute importance" values as the differences between the highest and lowest part-worth values of each attribute and normalized to sum to one. We set attribute importance according to an existing survey detailed in Kang et al (2015). In order to assign part-worth values to all attribute levels, here we set the part-worths of the highest and lowest levels of vehicle range to -1 and 1, respectively. The corresponding part-worth values of other attributes can then be assigned using attribute importance and assuming linearly increasing or decreasing part-worths with respect to the levels.
For given attribute levels, the vehicle demand can be calculated as:

$$vehicle\ demand = market\ size\ \times \frac{e^{v_j}}{\sum_{j' \in J} e^{v_{j'}}}, \tag{5}$$

where v_j is the utility of vehicle j, and J is the set of all three vehicles. Based on the demand of EVs, we can estimate the demand for charging service as

$$charging\ service\ demand = EV\ demand \times average\ charging\ frequency \times EV\ lifecycle. \quad (6)$$

Changing frequency is estimated using EV users' behavior data from Smart and Schey (2012) and ECOtality (2014). Average charging events per vehicle-day driven is 1.05. Further, 4.64% of charging events happen from public DC fast-charging stations and the rest are from home (Level 1) or charging stations (Level 2). Here we consider only DC fast-charging stations and assume a universal EV lifecycle of 10 years.

3 OPTIMIZATION AND PARAMETRIC STUDY

The model parameters are set as follows. Assume the market size of Ann Arbor is proportional to that of US. This gives us an estimated market of 5,800 consumers. For drive cycles, the standard EPA Highway Fuel Economy Drive Cycle is used. Look-up table of optimal charging station locations and average distances for Ann Arbor are pre-computed, as discussed in Section 2.3.

Table 6. Optimal decision values with $2.5M budget

	Variable	Scenario 1	Scenario 2	Scenario 3
Public policy	EV subsidy (per battery capacity)	$600	$369	$600
	Charging station subsidy	100%	100%	64%
	Electricity price cut	100%	100%	100%
	One-time tax cut	100%	100%	100%
Engineering	BEV #cells/branch (#branch)	159 (1)	175 (2)	172 (1)
	PHEV #cells/branch (#branch)	38 (3)	17 (3)	27 (4)
	BEV (PHEV) gear ratio	2.8 (5.0)	2.9 (7.0)	3.0 (7.0)
Operations	Number of charging stations	14	7	14
Marketing	EV price (before subsidy)	$23,969 ($35,969)	$26,540 ($42,785)	$16,614 ($29,594)
	PHEV price (before subsidy)	$24,105 ($32,707)	$21,647 ($24,014)	$19,688 ($27,838)
	Charging fee	$0	$0	$1 per kWh

Table 7. Responses with $2.5M budget

	Response	Scenario 1	Scenario 2	Scenario 3
Policy budget allocation	Total	$2.5M	$2.5M	$2.5M
	BEV subsidy	$0.39M	$1.19M	$0.60M
	PHEV subsidy	$1.51M	$0.47M	$1.36M
	Charging station subsidy	$0.38M	$0.53M	$0.34M
	Electricity price cut	$0.21M	$0.30M	$0.19M
	One-time tax cut	$10K	$12K	$8K
Market response	Emission	4.67e+10g	4.61e+10g	4.66e+10g
	BEV profit	$0.60M	$0.76M	$0.43M
	PHEV profit	$3.50M	$2.58M	$1.74M
	Station profit	$0	$0	$0
	Market share (BEV: PHEV: Gasoline)	1.2%:7.8%:91.0%	2.5%:8.6%:88.9%	1.4%:5.8%:92.7%

In this section, we examine the three business scenarios from Fig. 2, each with nine government budget levels: $0, $2.5M, $5M, $7.5M, $10M, $12.5M, $15M, $17.5M, and $20M. The currency used in the study is US dollar. We use the Sequential Quadratic Programing (SQP) algorithm for solving

the resultant nonlinear continuous optimization problems. These problems are solved iteratively until reaching equilibrium. Discrete variables, e.g., the number of battery cells and branches, are relaxed to be continuous during optimization and rounded to feasible values as a post-process. Due to non-convexity of the objective functions, we parallelize the SQP routine with ten independent initial points in order to avoid convergence to poor local solutions. The results thus obtained cannot be rigorously claimed as optimal, but they are sufficient for the purposes of this study.
Table 6 demonstrates the optimal decision for the three scenarios, with a budget level at \$2.5M. Table 7 shows the corresponding responses of these optimal decisions.

3.1 Summary of the Optimal Public Policy

We summarize the optimal allocation of government investment and the corresponding vehicle market shares for all budget levels and three scenarios in Fig. 4. We see that as the budget increases, the government tends to invest more in a BEV subsidy among all options. This is because BEV is the main contributor to emission reduction and thus its investment is the most effective for the government. However, this trend diminishes after the budget goes beyond \$10M. The reason for this could be that, while investment in BEV is cost-effective, other investments are proportionally required (e.g., the installment of charging stations) to keep the utility (and thus the market share) of BEV increasing.

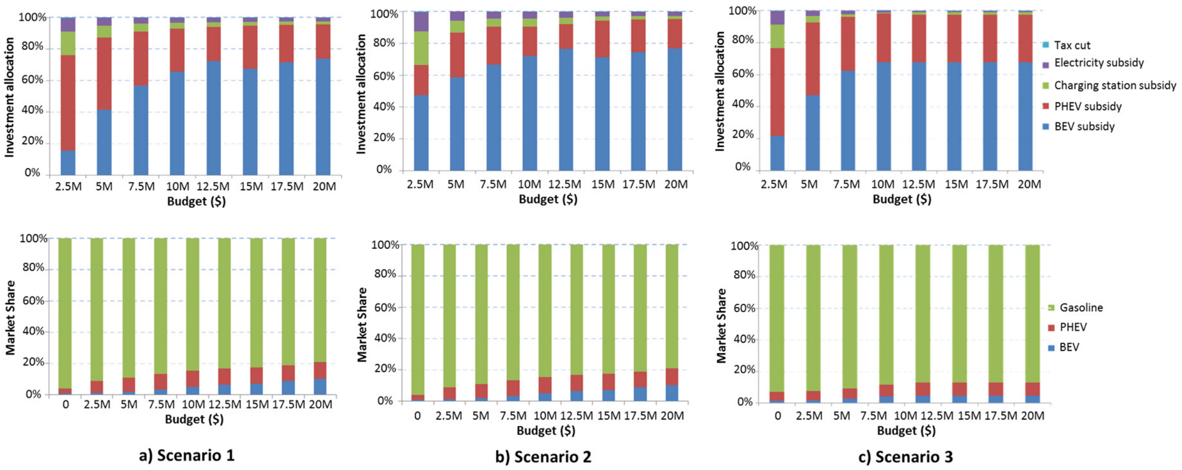


Figure 4. Investment allocation and market share

3.2 Parametric Study on Budget Level

We derive the optimal decisions for all three scenarios and nine budget levels to investigate how the budget levels affect emission and profit (BEV + PHEV + charging stations). The results are shown in Fig. 5.

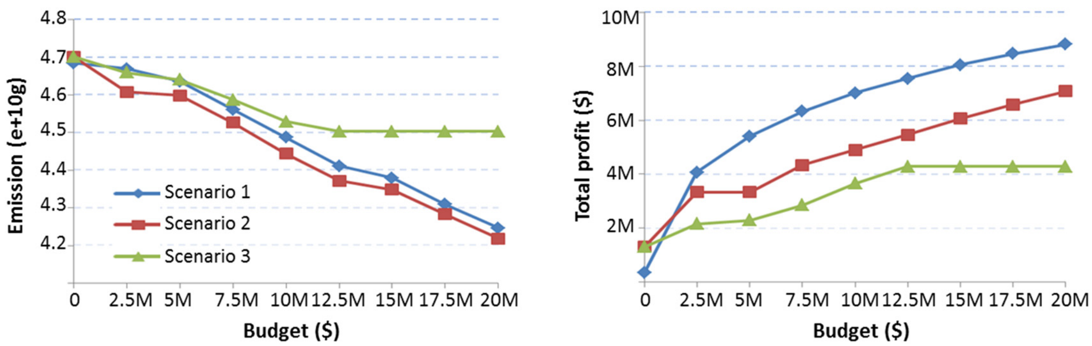


Figure 5. Parametric study for budget

We see that the all-in-one and the two-stakeholder scenarios have a similar trend in emission reduction and profit along budget allocation numbers, while in the three-stakeholder scenario, both objectives stop improving when the budget is greater than \$12.5M. We note that for the first two scenarios, the budget limit is always met at the optimal public policy decision, meaning that all government money

is put into use in order to yield the best outcome. However, in the third scenario with a budget greater than $12.5M, the government will not spend the entire budget in its optimal decision. The reason is as follows: We notice that at $12.5M, government subsidies for the manufacturer and incentives for consumers have reached their upper bounds. In this situation, there exist two possibilities for the government to spend the rest of its money: Increasing subsidy for charging stations would only result in higher charging service profit; increasing the EV market share would lead to more subsidy for the manufacturer and the consumers and thus further reduce emissions. However, in the three-stakeholder scenario, market share is affected only by the manufacturer and the charging service, rather than government subsidy. This is why at equilibrium the optimal policy will not spend all the allocated budget. With the same settings, the other two scenarios yield much better outcomes, in terms of both emissions reduction and total profit. This result raises an interesting hypothesis that if the government takes more control of the EV market, it can deploy its investment more effectively.
The all-in-one scenario is a multi-objective problem (i.e., emissions vs. total profit) and we can examine the impact of different budget allocations on the Pareto tradeoff curve. The Pareto curves in Fig. 6 show how tradeoffs are sensitive to budget levels. The blow-up in the bottom right shows the tradeoff at $7.5M budget in more detail.

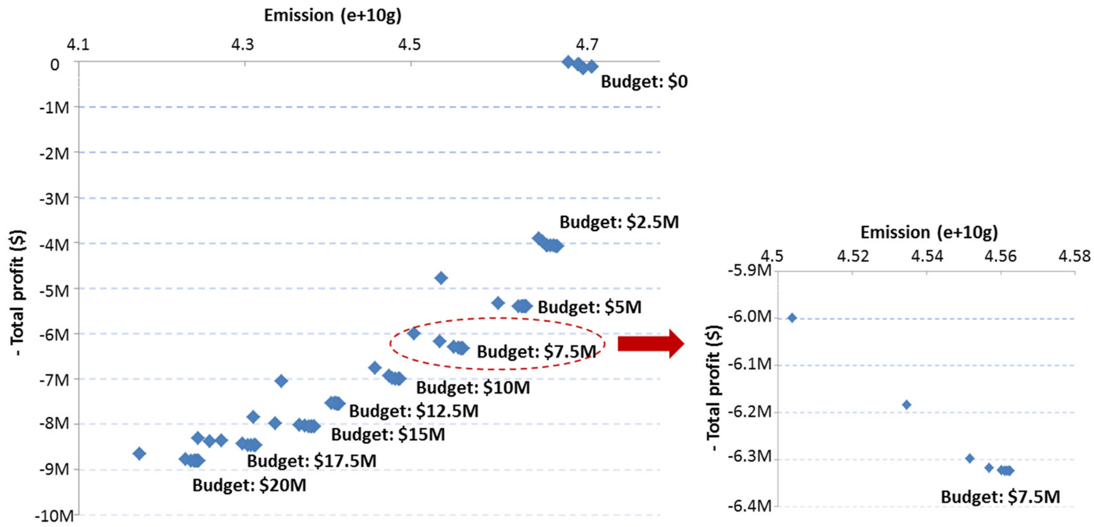


Figure 6. Pareto curves for the all-in-one scenario

4 CONCLUSION

We presented a multidisciplinary framework to analyze quantitatively the effect of government public policies on the EV market, through modeling the decisions of the manufacturer and charging station operator and the resulting consumer demand. We examined three scenarios for all stakeholders in the market to reach equilibrium.
There are two interesting findings from this study. First, we see that with an increasing budget but lower than $10M, the government should spend its increasing money allocation on BEV subsidies for emissions reduction purposes. When the budget increases beyond $10M, investment on infrastructure (e.g., charging stations) becomes necessary in order to keep the BEV utility high. Second, by comparing equilibrium outcomes from three scenarios, we showed that the government may deploy its investment more effectively when it has more control of the EV market, e.g., when it is able to make decisions on EV and charging service design.
In summary, the presented framework enables a holistic view of the EV market and allows policy makers to examine the impact of subsidy budget levels and policies while taking all stakeholders' interest into account. Next steps that can improve the value of this work include (i) performing conjoint analysis surveys to derive more realistic demand models for major EV markets; (ii) allowing more competitors, e.g., more manufacturers and charging station providers as well as a variety of EVs, in the game model; (iii) examining policy differences across different types of cities to understand how would city size, traffic conditions, and consumer preference in different nations or cities affect EV policies.

REFERENCES

AMESim. (2014) LMS Imagine.Lab AMESim, www.plm.automation.siemens.com (Nov 2014).
ECOtality. (2014) The EV Project, www.theevproject.com.
Kang, N., Feinberg, F. M., and Papalambros, P. Y. (2015) Integrated Decision Making in Electric Vehicle and Charging Station Location Network Design, Journal of Mechanical Design, DOI: 10.1115/1.4029894.
Mock, P. and Yang, Z. (2014) Driving Electrification: A Global Comparison of Fiscal Incentive Policy for Electric Vehicles, The International Council of Clean Transport, www.theicct.org (Nov 2014).
Smart, J. and Schey, S. (2012) Battery Electric Vehicle Driving and Charging Behavior Observed Early in the EV Project, SAE International Journal of Alternative Powertrains, Vol. 1, No. 1, pp. 27–33.
Tansel, B. C., Francis, R. L., and Lowe, T. J. (1983) State of the Art—Location on Networks: A Survey. Part I: The p-Center and p-Median Problems, Management Science, Vol. 29, No. 4, pp. 482-497.

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