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INTEGRATED DECISION MAKING IN ELECTRIC VEHICLE AND CHARGING STATION LOCATION NETWORK DESIGN

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ABSTRACT

A major barrier in consumer adoption of electric vehicles (EVs) is 'range anxiety,' the concern that the vehicle will run out of power at an inopportune time. Range anxiety is caused by the current relatively low electric-only operational range and sparse public charging station infrastructure. Range anxiety may be significantly mitigated if EV manufacturers and charging station operators work in partnership using a cooperative business model to balance EV performance and charging station coverage. This model is in contrast to a sequential decision making model where manufacturers bring new EVs to the market first and charging station operators decide on charging station deployment given EV specifications and market demand. This paper proposes an integrated decision making framework to assess profitability of a cooperative business models based on a multidisciplinary optimization model that combines marketing, engineering, and operations. This model is demonstrated in a case study involving battery electric vehicle design and direct-current fast charging station location network in the State of Michigan. The expected benefits can motive both government and private enterprise actions.

1. INTRODUCTION

In the Electric vehicle (EV) market one can identify five key players besides the comsumers themselves [1]: Original Equipment Manufacturers (OEMs) assemble vehicles and sell them to consumers; battery manufacturers supply batteries to OEMs; utilities supply electricity to charging stations; charging station manufacturers supply Electric Vehicle Supply Equipment (EVSE) to utilities; and governments support all related activities through a variety of policies.

EVs face several consumer adoption barriers such as vehicle operating range, vehicle cost, perceived safety, unusual emergency situations, reliability, vehicle size and performance, infrastructure support, long charging time, high charging cost, and long payback period expectations [1, 2]. The individual market players mentioned above are expending significant effort to overcome such barriers. In this paper, we adopt the argument that to overcome these barriers effectively, the market players must use a holistic approach to develop cooperatively integrated business models rather than just pursue their individual business models [3]. In this spirit, we present a mathematical formulation of an integrated decision-making (optimization) framework that can support an integrated business model. Some of the market players are already cooperating in the market using business to business (B2B) models. For example, cooperation of OEMs and battery manufacturers or cooperation of utilities and charging station manufacturers are common. In the current study we address a cooperative business model between two groups: EV manufacturers (i.e., OEMs and battery manufacturers) and charging station operators (i.e., utilities and charging station manufacturers).

A major barrier to consumer adoption is *range anxiety*. The consumer perception of its importance depends not only on the

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actual operating range determined by the design of the vehicle and its battery (vs. that of a conventional fuel vehicle) but also on the availability of charging stations and required charging times when the consumer plans a particular, possibly long, trip. Thus, consumers hesitate to buy EVs due to range anxiety, EV manufacturers hesitate to develop and produce EVs due to small market demand, and charging station operators hesitate to invest in charging infrastructure for the same reason [4].

Addressing range anxiety requires coordination of engineering business decisions by EV manufacturers and operation business decisions by charging station operators. For example, a short range vehicle in a market with ample charging stations may induce less range anxiety than a long range vehicle in a market with sparse charging stations. Interestingly, research shows that the average daily driving range in the US is less than 20 miles [5, 6], and so range anxiety may be due more to a psychological need for security in an occasional long trip. Appealing to consumers through, say, joint advertising, for both EV performances and public charging stations coverage as a 'bundle' could be more effective in EV technology adoption. This approach could also address the issue of high initial vehicle cost due to a large battery pack that accounts for almost half of total consumer vehicle cost [7].

EV manufacturers and charging station operators can partner to identify optimal 'system' balance between vehicle performance and charging station infrastructure to maximize market share or profit for both parties. A cooperative example in the US is the EV project supported by the U.S. Department of Energy engaging partners such as ECOtality, Nissan LEAF, and Chevrolet Volt in major states [8]; the ChargePoint program supported by Coulomb Technologies is a cooperation among Chevrolet, Ford, and Smart USA [9]; Reliant Energy is working with Nissan in Houston, and Southern California Edison is working with Ford in California. Such cooperations typically focus only on funding for installation of EVSEs in target EV markets rather than the broader cooperation suggested here.

In this study, we consider a charging infrastructure with direct current (DC) fast charging stations for commuting between major cities or trips longer than the range offered by a typical EV in the current market. EVs generally use three types of charging modes (or stations), Level 1, Level 2, and DC fast. It takes at least three hours to recharge a battery using Levels 1 or 2, while DC fast can recharge a battery to 80% capacity (for safety reasons) within 30 minutes. DC fast charging stations are considered promising for a future public charging infrastructure, but there were only154 stations in the US as of 2012 [10]. The profitability of a DC fast charger station infrastructure investment is uncertain and such investments have not been made [11].

This paper presents an integrated decision making framework combining EV design and charging station location network design problems. EV manufactures decide on vehicle price and attributes such as range, charging time, MPGe (miles per gallon gasoline equivalent), top speed, and acceleration (0 to 60 mph). Charging station operators decide on charging fee, how many stations to build, and where these stations should be located considering EV range offered by the manufacturer. The optimization objective is to maximize overall profit, and it is assumed that EV manufacturers and charging station operators invest together and share the profits. Optimization results show that a cooperative business model (i.e., integrated decision making for overall profit) is more profitable than a sequential business model (i.e., engineering decision making and then operating decision making for each player's profit) for both partners.

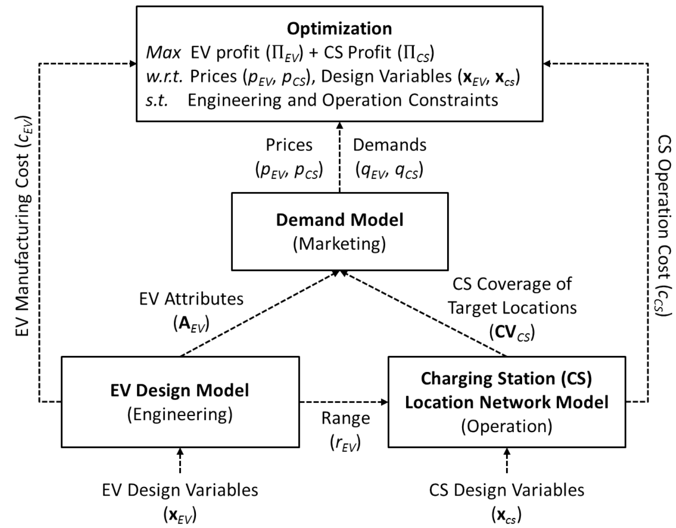

FIGURE 1. FRAMEWORK OF DECISION MAKING

The remainder of the paper is organized as follows. Section 2 introduces the integrated decision making framework and associated models. Section 3 presents an implementation case study for an EV market in the State of Michigan. Sections 4 and 5 discuss results, conclusions and limitations.

2. INTEGRATED DECISION MAKING FRAMEWORK

2.1. Framework

The decision making framework consists of three models for marketing, engineering and operations with shared decision variables. The framework and the detailed nomenclature are given in Fig. 1 and Table 1, respectively.

The EV design model represents the engineering problem with EV design variables ($\mathbf{x}_{EV}$) such as battery ($\mathbf{B}_{EV}$), motor ($\mathbf{M}_{EV}$), and gear (G_{EV}) designs as variable inputs; and EV attributes ($\mathbf{A}_{EV}$) such as range (r_{EV}), MPGe (mpg_{EV}), top speed (sp_{EV}), acceleration (acc_{EV}), and charging time (ct_{EV}) as outputs. These outputs are used as inputs to the marketing and operation models.

The DC fast charging station (CS) location network model

TABLE 1. NOMENCLATURE FOR SYSTEM DESIGN

Models	Variables and Responses
Profit optimization and demand models	Π_{EV}: EV profit Π_{CS}: CS profit p_{EV}: EV price p_{CS}: Charging fee q_{EV}: EV demand q_{CS}: CS demand c_{EV}: EV manufacturing cost c_{CS}: CS operations cost c_{EC}: Electricity cost
EV design model	$\mathbf{x}_{EV}$: EV design variables $\mathbf{B}_{EV}$: Battery design variables $\mathbf{M}_{EV}$: Motor design variables G_{EV}: Gear ratio $\mathbf{A}_{EV}$: EV attributes r_{EV}: Range mpg_{EV}: MPGe sp_{EV}: Top speed acc_{EV}: Acceleration ct_{EV}: charging time
CS location network	$\mathbf{x}_{CS}$: CS design variables $\mathbf{L}_{CS}$: CS locations N_{CS}: Number of CS CV_{CS}: CS coverage of target locations

represents the operations problem with CS design variables ($\mathbf{x}_{CS}$) such as number (N_{CS}) of stations and location ($\mathbf{L}_{CS}$) of stations as variable inputs, EV range (r_{EV}) as input from engineering, and charging station coverage (CV_{CS}) as the output. This output is used as input to the marketing model. Coverage is defined as the percentage of possible paths a consumer can drive from her origin (i.e., home) without running out of power by using DC fast charging stations.

The marketing model predicts EV and charging station demands (q_{EV}, q_{CS}) using the EV attributes ($\mathbf{A}_{EV}$) from the engineering model and charging station coverage (CV_{CS}) from the operations model as inputs, as well as EV price (p_{EV}) and charging fee (p_{CS}) as variable inputs.

The optimization objective is to maximize overall profit ($\Pi_{EV} + \Pi_{CS}$) from EVs and charging stations with respect to the variables: EV price (p_{EV}), charging fee (p_{CS}), EV design ($\mathbf{x}_{EV}$), and charging station design ($\mathbf{x}_{CS}$).

The overall optimization equation is stated as follows.

$$\begin{aligned} \max_{\bar{\mathbf{x}}} \quad & \Pi_{EV} + \Pi_{CS} \\ & = (p_{EV} - c_{EV}) q_{EV} + (p_{CS} - c_{EC}) q_{CS} - c_{CS} \end{aligned} \tag{1}$$

with respect to

$$\begin{aligned} \bar{\mathbf{x}} &= [p_{EV}, p_{CS}, \mathbf{x}_{EV}, \mathbf{x}_{CS}] \\ \mathbf{x}_{EV} &= [\mathbf{B}_{EV}, \mathbf{M}_{EV}, G_{EV}] \\ \mathbf{x}_{CS} &= [\mathbf{L}_{CS}, N_{CS}] \end{aligned} \tag{2}$$

subject to

$$lb \leq \bar{\mathbf{x}} \leq ub \tag{3}$$

$$\mathbf{g}(\mathbf{A}_{EV}) \leq 0 \tag{4}$$

where

$$\mathbf{A}_{EV} = [r_{EV}, mpg_{EV}, sp_{EV}, acc_{EV}, ct_{EV}] \tag{5}$$

$$[c_{EV}, c_{CS}] = f_c(\mathbf{x}_{EV}, \mathbf{x}_{CS}) \tag{6}$$

$$[q_{EV}, q_{CS}] = f_q(p_{EV}, p_{CS}, \mathbf{A}_{EV}, CV_{CS}) \tag{7}$$

$$\mathbf{A}_{EV} = f_{EV}(\mathbf{x}_{EV}) \tag{8}$$

$$CV_{CS} = f_{CS}(\mathbf{x}_{CS}, r_{EV}) \tag{9}$$

where $\bar{\mathbf{x}}$ in (2) are decision variables, (3) are boundary constraints, and (4) are inequality constraints for EV attributes as shown in Table 3 in detail. Furthermore, f_c, f_q, f_{EV}, and f_{CS} are

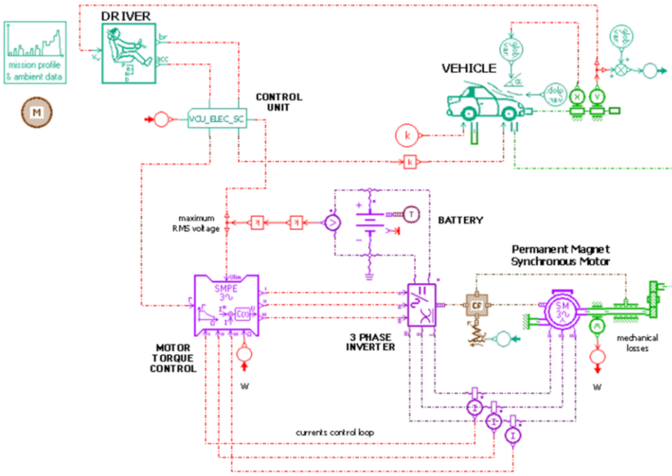

FIGURE 2. ENGINEERING SIMULATION MODEL

cost model, demand model, engineering model, and operations model, respectively. Each model is explained in more detail in the next sections.

2.2. Engineering Model

The engineering performance model of a Battery Electric Vehicle (BEV), f_{EV}, in Eqn. (8) is built using the AMESim software subsystem models include analytical expressions from the AMESim libraries [12]. Previous research showed that analytical models of EV systems are appropriate for efficient system-level simulations in the early design stage, and their adequate fidelity has been assured through comparison with finite element models or laboratory measurements [13–15].

The engineering model here consists of driver, control unit, motor torque control, battery, inverter, permanent magnet synchronous motor, and vehicle models as shown in Fig. 2. The overall architecture and vehicle parameters are for a vehicle similar to the Nissan Leaf. The subsystems designed in the study are lithium ion battery, permanent magnet synchronous motor, and gearing. Six design variables and their lower and upper bounds are summarized in Table 2. Inequality constraints on five attributes (responses) are summarized in Table 3.

Battery We use the simple battery model shown in Fig. 3 where *OCV* is open circuit voltage, r is internal resistance, I is current, *CF* is filtering capacitance, and U is the output voltage. Based on this model, state of charge (SOC), output voltage, and heat flow rate (i.e., the thermal losses) are computed as outputs of the simulation.

Battery design variables are the number of cells in series in one branch and the number of branches in parallel affect, and

TABLE 2. DESIGN VARIABLES OF ENGINEERING MODEL

System	Symbol	Design variables	Lower bound	Upper bound
Battery	n_s	Number of cells in series in one branch	50	150
	n_p	Number of branches in parallel	1	4
Motor	L_d	Stator inductance of the d-axis	1.35mH	5.40mH
	L_q	Stator inductance of the q-axis	1.65mH	6.60mH
	R_s	Stator resistance	0.001Ω	0.1Ω
	p	Number of pole pairs	1	4
Gear	G	Gear ratio	1	15

TABLE 3. RESPONSES AND CONSTRAINTS OF ENGINEERING MODEL

Response	Constraint
Range	$\geq$70 miles
Battery charging time	$\leq$50 minutes
MPGe	$\geq$80 MPGe
Top speed	$\geq$70 mph
Acceleration (0 to 60 mph)	$\leq$20 sec

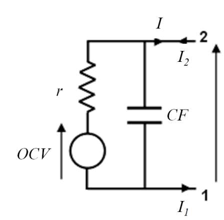

FIGURE 3. BATTERY MODEL [12]

they are used to calculate the following battery characteristics:

$$C_{bt} = C_{cell} \cdot n_p \tag{10}$$

$$CF_{bt} = CF_{cell} \cdot \frac{n_p}{n_s} \quad (11)$$

$$OCV_{bt} = OCV_{cell} \cdot n_s \quad (12)$$

$$r_{bt} = r_{cell} \cdot \frac{n_s}{n_p} \quad (13)$$

Here n_s and n_p are the number of cells in series in one branch and the number of branches in parallel, respectively; C_{bt} is capacity of battery, C_{cell} is capacity of a cell, CF_{bt} is filtering capacitance of battery, CF_{cell} is filtering capacitance of a cell, OCV_{bt} is open circuit voltage of battery, OCV_{cell} is open circuit voltage of a cell, r_{bt} is internal resistance of battery, and r_{cell} is internal resistance of a cell. Since OCV_{cell} and r_{cell} are affected by SOC, OCV_{cell} and r_{cell} are computed by linear interpolation of available experiment data. All battery cell parameter values in the above equations are based on Nissan Leaf battery cell tests [16].

From the battery characteristics above, SOC, output voltage, and heat flow rate are computed:

$$\frac{dSOC}{dt} = 100 \cdot \frac{I_2}{C_{bt}} \quad (14)$$

$$\frac{dU}{dt} = \frac{I_2 - \frac{U - OCV_{bt}}{r_{bt}}}{CF_{bt}} \quad (15)$$

$$dh = \frac{(U - OCV_{bt})^2}{r_{bt}} \quad (16)$$

where U is the output voltage and dh is heat flow rate based on Joule's losses.

Permanent Magnet Synchronous Motor The motor model outputs, torque and heat flow rate, are computed using permanent magnet flux linkages, stator inductance, and the number of pole pairs as design variables.

The stator flux linkages are computed from the equations

$$\varphi_d = L_d I_d + \sqrt{\frac{3}{2}} \varphi_{PM} \quad (17)$$

$$\varphi_q = L_q I_q \quad (18)$$

where φ_{PM} is permanent magnet flux linkage, φ_d and φ_q are stator flux linkages of the d-axis and q-axis, respectively, L_d and L_q are stator inductance of the d-axis and q-axis, respectively, and I_d and I_q are stator currents of the d-axis and q-axis, respectively. The toque and heat flow rate are then computed from

$$T = p(\varphi_d I_q - \varphi_q I_d) \quad (19)$$

$$dh = R_s I_d^2 + R_s I_q^2 \quad (20)$$

where T is the torque, p is the number of pole pairs, dh is heat flow rate, and R_s is stator resistance.

Gear Ratio and Driving Cycle For the rotary mechanical gear ratio we use the equations

$$w_{motor} = G \cdot w_{axle} \quad (21)$$

$$T_{axle} = G \cdot T_{motor} \quad (22)$$

where w_{motor} is motor velocity, w_{axle} is axle velocity, T_{motor} is motor torque. normal driving cycle Range and MPGe are computed on the EPA Highway Fuel Economy Cycle, the standard way to compare EV performance in the market. Top speed and acceleration are computed for straight line running. Vehicle mass, except for battery mass, and drag coefficient follow Nissan Leaf specifications [7, 17]. The relation of driving range and the size of battery pack is nonlinear because larger battery mass diminishes driving range while more battery capacity improves driving range at the same time [18]. Battery charging time is computed as a linear function of battery capacity, where 30 minutes correspond to recharging 80% of 24kWh, as for a Nissan Leaf battery using a fast DC charger [7].

EV Manufacturing Cost Battery pack cost is a variable cost in the EV manufacturing cost model, the remaining costs considered as fixed. Battery cost currently ranges from \$300 to \$600 per kWh; it is decreasing with time and is expected to reach \$250 per kWh by 2020 [19, 20]. In this study we used \$500/kWh for battery cost and assumed that fixed cost after a government subsidy is \$8,000, resulting to a manufacturing cost for an EV with 24kWh battery estimated as \$12,000.

2.3. Operation Model

Two different types of charging station coverage are used in the study: *Path coverage*, a charging station attribute in the consumer demand model; and *flow coverage*, an objective of location modeling. Path coverage is defined as the percentage of possible paths (i.e., round trips) a consumer can drive without running out of power. We assume that consumers fully charge the EV in their home before driving to a destination. Possible paths are defined as combinations of paths from a city to another city in a state or country. For example, if the coverage is 100%, a consumer can drive from one of the select cities to any other select city without concern for running out of power; if the coverage is 50%, a consumer can drive only 50% of the paths between cites without being concerned. Flow coverage is defined as the percentage of total traffic flows that can be recharged. Since each possible path has different amount of traffic flow, a path with more flow should have more relative weight on charging station location decisions. Maximizing flow coverage is the overall desirable goal. However, a consumer cares about his vehicle recharge need rather than the total recharged flow volume. This is why flow coverage must be mapped into path coverage (i.e., every path has the same weight) to be used in the consumer demand model.

Location Network Model A location model for fast DC charging stations, f_{CS}, is established using practices in geographical analysis. Hodgson (1990) first proposed the Flow Capturing Location-allocation Model (FCLM) [21]. In this study, we adopt a variant called the Flow Refueling Location Model (FRLM) [22–27] that has been widely used to find optimal location of refueling facilities for alternative-fuel vehicles with limited range.

The standard FRLM [22] is used in the study resulting in a mixed-integer linear programming problem to maximize the flow coverage with respect to location of charging stations given the number of stations and EV range, see Eqn. (9).

$$\max_{\mathbf{x},\mathbf{y},\mathbf{v}} \sum_{q\in Q} f_q y_q \tag{23}$$

Subject to

$$\sum_{h\in H} b_{qh} v_h \geq y_q \quad \forall q \in Q \tag{24}$$

$$a_{hk} x_k \geq v_h \quad \forall h \in H;\ k \in K \tag{25}$$

$$\sum_{k\in K} x_k = p \tag{26}$$

$$x_k \in \{0,1\} \quad \forall k,h,q \tag{27}$$

$$0 \leq v_h \leq 1 \quad \forall h \tag{28}$$

$$0 \leq y_q \leq 1 \quad \forall q \tag{29}$$

where

q is the index of O-D pairs (O is an origin, D is a destination, and O-D pairs indicate the shortest paths for each pair)

Q is the set of all O-D pairs

f_q is the flow volume on the shortest path between O-D pair q

y_q = 1 if $f_q$is captured, 0 otherwise

k is a potential station location

K is the set of all potential station locations

h is the index of combinations of stations

H is the set of all potential station combinations

b_{qh} = 1 if station combination h are open, 0 otherwise

v_h = 1 if all stations in combination h are open, 0 otherwise

a_{hk} = 1 if station k is in combination h, 0 otherwise

x_k = 1 if a station is located at k, 0 otherwise

p is the number of stations to be located.

The objective function (23) maximizes the total flow volume (flow coverage % can also be used) that can be recharged with p stations. The flow between two cities, f_q, is calculated by a gravity model based on the city population and path distance (i.e., flow = population of city A x population of city B / path distance^2). In constraints (24), at least one eligible combination of stations h should be open for path q to be recharged. In constraints (25), v_h should be held to zero unless all stations k in combination h are open. In constraints (26), p stations are required to be built. In (27), the charging station location variables x_k are defined as binary variables. Although v_h and y_q are also defined as binary variables, they can be relaxed as continuous variables with lower and upper bounds in (28) and (29). This trick can find an all-integer solution by reducing the number of required binary variables. More detail explanation can be found in [22].

Before using the FRLM model, we must pre-generate all combinations of stations, H, that can recharge a path following six steps [24]:

1. Generate the shortest path for all O-D pairs q, and establish an empty master list of all combinations h.
2. Generate a temporary list of all station combinations h of nodes on path q.
3. Remove station combinations that cannot recharge an EV of the given on path q.
4. If any combination h is still on the list for path q:
   Add it to the master list of station combinations if it is not already there.
   Record b_{qh}=1 if station combination h can recharge path q and 0 otherwise.
   Record a_{hk}=1 if station k is in combination h, or 0 otherwise.
5. Repeat Steps 2-5 for all paths q.

For this location problem, Lim and Kuby (2010) have shown that use of a genetic algorithm (GA) can have better performance to find global optimum than a mixed-integer linear programming (MILP) solution algorithm. It the present study, we use GAs to solve the location optimization problem with variables being the number of stations, station locations, and EV range, and output the optimal flow coverage. This optimal flow coverage is converted into path coverage and used as a charging station attribute in the consumer demand model (see Section 2.4).

Fast DC Charging Station Cost The cost of fast DC charging station infrastructure can be decomposed into variable cost, such as electricity cost, and fixed cost such as installation, equipment and maintenance cost. Electricity cost varies according to the charging time from 8 to 17 cents per kWh [28]. Here we used 10 cents per kWh. Fixed costs depend on the condition of stations. Here we used \$75,000 for installation and equipment costs, and \$5,500 for maintenance cost for one year [11]. We evaluate profit and costs over a five-year period. We assume that two chargers are installed per charging station.

2.4. Marketing Model

Hierarchical Bayesian (HB) choice-based conjoint [30,31] is used for building a heterogeneous marketing demand model, f_M. Choice data are gathered using choice-based conjoint analysis. Individual-level discrete utility functions are estimated using the HB choice model. Spline curves are fitted to the individual-level posterior modes for each conjoint part-worth. Market demand is then calculated with choice probabilities based on individual-level utility functions and market potential.

The individual level discrete utility v_{ij} is a linear function of discrete levels of attributes and defined as,

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} z_{jkl} \tag{30}$$

where z_{jkl} are binary dummy variables indicating alternative j possesses attribute k at level l, and β_{ikl} are the part-worth coefficients of attribute k at level l for individual i [32].

The HB choice model has two levels. At the upper level, an individual's part-worths, β_i, have a multivariate normal distribution, $\beta_i \sim N(\theta, \Lambda)$, where θ is a vector of means of the distribution of individuals and Λ is the covariance matrix of that distribution. At the lower level, choice probabilities for a logit model are used:

$$P_{ij} = \frac{e^{v_{ij}}}{\sum\limits_{j' \in J} e^{v_{ij'}}} \tag{31}$$

where P_{ij} indicates probability individual i chooses option j from a set of alternatives J. Markov Chain Monte Carlo (MCMC) is used to estimate the individual's part-worth. The utility function in Eqn. (30) based on the HB choice model cannot be used for continuous design decisions because the function is discrete. We calculate interpolated values of discrete part-worths using cubic splines so that choice probabilities for continuous design decisions can be estimated.

Market demand is calculated based on individual level choice probabilities as

$$q_j = \frac{1}{I} \sum_{i=1}^{I} s P_{ij} \tag{32}$$

where q_j is market demand of option j, s is the potential market size, and I is total number of individuals. This averaging of individual market demands is used for optimization. However, when we compare demands of different design decisions, each individual level market demand should be compared. More detail description of marketing demand models for design decisions can be found in [33, 34].

EV demand is computed with Eqn. (32) using the attributes and levels of EV and charging station shown in Table 4, selected based on previous research and the current EV market [35].

Public charging station demand is estimated sequentially based on EV demand. This is because EV drivers are potential consumers of charging stations during the EV and charging station life cycles. Many scenarios of charging behavior can be considered [29]. Here we estimate fast charging events based on observed data of EV users from a particular EV project [6], which showed that the mean number of charging events per vehicle-day driven is 1.05, and 18% of charging events are away from a home location. We assume that 30% of charging events away from home would take place in the fast DC charging stations. We estimate charging station demand over five years to evaluate profitability of the infrastructure investment. While the average

TABLE 4. ATTRIBUTE LEVELS AND IMPORTANCE

Attributes	Unit	Level					Importance
		1	2	3	4	5	
Charging station coverage	%	0	25	50	75	100	38.8%
Charging fee	$	0	5	10	15	20	14.1%
Charing time	minutes	10	20	30	40	50	2.1%
Vehicle price	$	20K	30K	35K	40K	50K	25.7%
Range	miles	70	100	130	160	200	9.1%
Fuel efficiency	MPGe	70	100	130	160	200	4.7%
Top speed	mph	70	80	90	100	110	3.1%
Acceleration	sec	8	10	12	14	16	2.4%

TABLE 5. OPTIMAL DECISION VALUES

Model	Variable	Optimal value
Marketing	Vehicle price	$49,844
	Charging fee	$0.07
Engineering	Number of cells in series in one branch	122
	Number of branches in parallel	1
	Stator inductance of the d-axis	0.00272
	Stator inductance of the q-axis	0.00332
	Stator resistance	0.03032
	Number of pole pairs	3
	Gear ratio	3.29
Geography	Number of stations (out of 29 candidates)	7
	Stations locations	See Fig. 4

value of individual-level demand is used for optimization, each individual-level demand is used for comparison of different design decisions.

3. CASE STUDY: SOUTHEAST MICHIGAN MARKET

The proposed decision making framework is applied on a study of EV market in Southeast Michigan. In the operation model, the relevant portion of Michigan's highway network used to to determine possible paths and flows is shown in Fig. 4. There are no public DC fast charging stations in Michigan at the time of this writing. Nineteen cities are selected based on their population with some neighboring cities grouped and treated as a single one. Circle nodes indicate cities where charging stations exist, size of circles represents the size of population, lines indicate shortest highway paths, numbers indicate path distances between nodes, and triangles indicate additional junctions needed for charging stations because of limited BEV range. A total of 29 locations of cities and junctions are candidates for charging station locations resulting in 171 possible paths between 19 cities in this network (19×18 / 2 = 171).

For the marketing demand model, 203 US respondents were surveyed using Amazon's Mechanical Turk [36] and Sawtooth Software [31]. The respondents consisted of 61% males and 39% females; 29% were 18 to 24 years of age, 46% were 25 to 34 years of age, 12% were 35 to 44 years of age, and 13% were more than 45 years of age, with 53% of all respondents stating that they were likely to purchase an EV in the future. Table 4 shows the average relative importance of the attributes in the model based on estimated part-worths of attributes levels. The charging station attributes are evidently important in consumer choices. For MCMC, every tenth draw from the last 50,000 (of 100,000 total) draws were used to obtain the individual's parameter. BEV market size of Michigan was assumed to be 920 based on the total 2013 US BEV sales of 46,000 [37] devided by 45 states. Two EV competitors operating in Michigan were assumed in computing market share.

Matlab's implementation of the GA [38] was used to solve the mixed integer optimization problem of Eqn. (1). The computed optimal decision values are summarized in Table 5. Response values for these optimal decision values are shown in Table 6. Note that market responses correspond to the average values of 203 cases using individual-level demand models. Since we considered a heterogeneous market in demand modeling, market response are represented by the distribution of individual responses.

The results indicate that the charging station operator must build seven stations (out of 29 candidates) located in six cities (i.e., Wyoming, Livonia, Southfield, Rochester hills, Shelby and Macomb, and Detroit) and in one junction between Ann Arbor and Dearborn, see Fig. 4. The relationship between flow coverage and path coverage is shown in Fig. 5 with 85.2 miles of

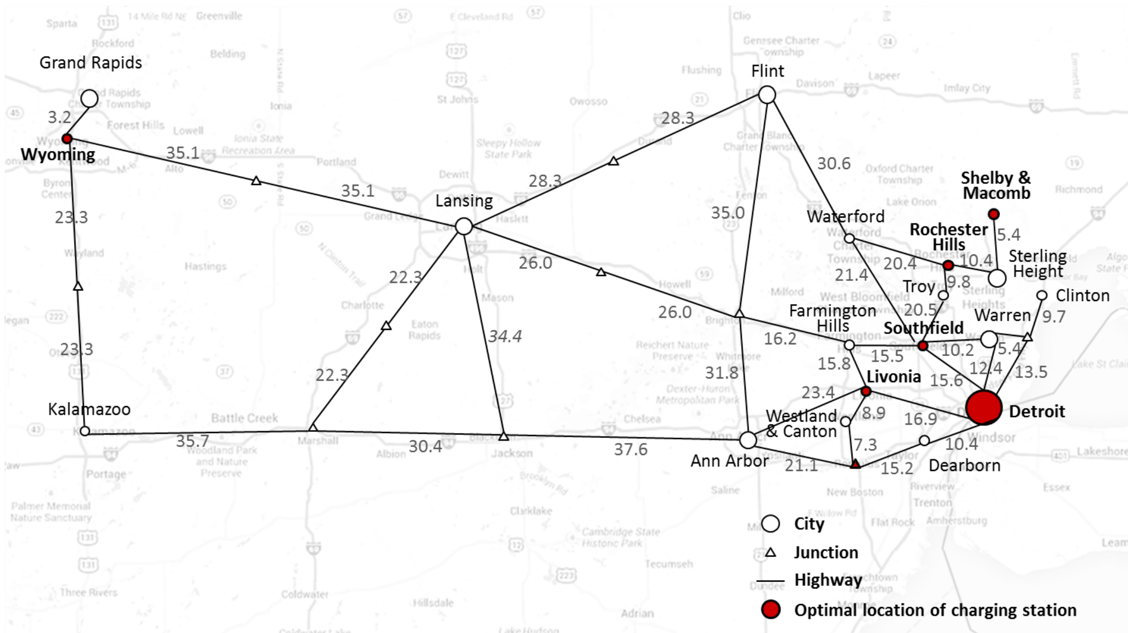

FIGURE 4. MICHIGAN HIGHWAY NETWORK AND OPTIMAL LOCATIONS OF CHARGING STATIONS

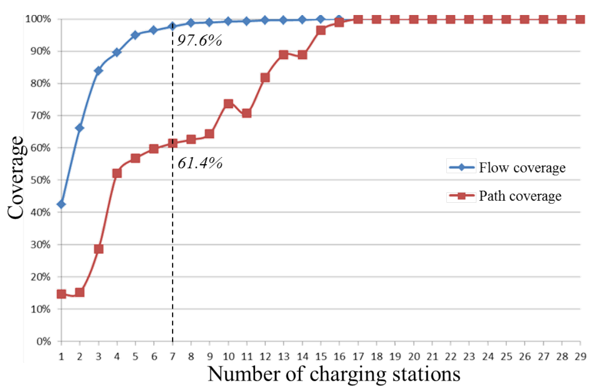

FIGURE 5. CHARGING STATIONS COVERAGE FOR 85.2 MILES EV RANGE

range determined as optimal.

4. Discussion

Two different business models are compared in order to determine the value of a cooperative business model. The cooperative business model considers EV manufacturer and fast charging station operator as a single company and finds optimal decisions for EV and stations simultaneously by maximizing overall profit (i.e., EV profit + charging station profit). For this business model, EV manufacturers are encouraged to expand their business to charging station operations or partner with existing utilities or charging station manufacturers, sharing investment and profit. The second business model is a 'sequential' model similar to current practice, where the EV OEM designs EVs to maximize OEM profit, and the charging station provider makes location decisions for given EV designs to maximize operation profit.

Results for these two business models are compared in Table 7. Market responses are average values of 203 responses based on the individual demand model. The cooperative model gives higher overall profit and market share than the sequential model. In each comparison for the 203 market responses, 81% of cooperative business model cases had more profits and market share. The sequential model requires a higher range than the cooperative one. Also, a charging station operator would not build many charging stations and would need to charge higher fees than in the cooperative model. One may conclude that, under the modeling assumptions we have made, a non-cooperative business model will not improve the attractiveness of EVs to consumers.

We further observe that in the cooperative model the relatively smaller EV range is compensated by larger charging station coverage than in the sequential model. A balance between EV range and charging station infrastructure can effectively reduce consumer range anxiety. The cooperative model allows for more market share by supplying almost free charging and larger charging station coverage to consumers despite lower vehicle range than the sequential model. Since the cooperative model allows even negative profit of charging stations, attractive charging station attributes can boost EV adoption share, resulting in higher overall profit than the sum of the two positive individual

TABLE 6. RESPONSES OF OPTIMAL DECISIONS

	Response	Values
Market	Overall profit	$19.25M
	EV profit	$20.43M
	Station profit	-$1.18M
	Market share	65.0%
EV attributes	Vehicle price	$49,844
	Range	85.2miles
	MPGe	190.1
	Top speed	94.7mph
	Acceleration	19.0sec
Charging station attribute	Charging fee	$0.07
	Charging time	19.2m
	Path coverage	61.4%
	Flow coverage	97.6%

Note: Market response shown in this table is the mean of market response distribution.

TABLE 7. COMPARISON OF TWO BUSINESS MODELS

		Cooperative business model	Sequential business model
Market	Total profit	$19.25M	$6.94M
	EV profit	$20.43M	$6.75M
	Station profit	-$1.18M	$0.19M
	Market share	65.0%	22.5%
EV attributes	Vehicle price	$49,844	$49,977
	Range	85.2miles	107.5miles
	MPGe	190.1	195.16
	Top speed	94.7mph	116.4mph
	Acceleration	19.0sec	15.9sec
Charging station attributes	Number of charging stations	7	1
	Charging fee	$0.07	$20
	Charging time	19.2m	23.6m
	Path coverage	61.4%	16.4%
	Flow coverage	97.6%	43.0%

Note: Market response shown in this table is the mean of market response distribution.

profits from EV and charging stations in the sequential model. This is an example of examining a product-service system in an integrated business model [39].

5. CONCLUSION

The proposed integrated decision making framework allows quantification of the tradeoffs among various business models for the EV market. A cooperative business model presents more advantages than the existing non-cooperative business model. The results clearly depend on the modeling assumptions made; however, these are generally sufficiently plausible to support the case for a cooperative approach to improve consumer adoption of EVs.

In future work, the reliability of the results should be explored through parametric and sensitivity analysis. Southeast Michigan residents should be surveyed to build the marketing model for representing consumer preferences of the target market. The charging station coverage for each city also should be considered rather than a single coverage value for all cities. Perhaps most interestingly, a government policy model should be integrated in the proposed framework to explore quantitatively how government incentives and regulations affect market decisions.

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