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AUTONOMOUS ELECTRIC VEHICLE SHARING SYSTEM DESIGN

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ABSTRACT

Car-sharing services promise “green” transportation systems. Two vehicle technologies offer marketable, sustainable sharing: Autonomous vehicles eliminate customer requirements for car pick-up and return, and battery electric vehicles entail zero-emissions. Designing an Autonomous Electric Vehicle (AEV) fleet must account for the relationships among fleet operations, charging station operations, electric powertrain performance, and consumer demand. This paper presents a system design optimization framework integrating four sub-system problems: Fleet size and assignment schedule; number and locations of charging stations; vehicle powertrain requirements; and service fees. A case study for an autonomous fleet operating in Ann Arbor, Michigan, is used to examine AEV sharing system profitability and feasibility for a variety of market scenarios.

1. INTRODUCTION

Car-sharing services offer a sustainable transportation alternative with the potential to reduce emissions, congestion, parking demand, and rider cost, while increasing user mobility and convenience [1]. The car-sharing market in the U.S. had an annual 38% membership increase in 2013 [2]. A typical service like Zipcar [3] uses five steps for a two-way trip service: Become a member, reserve a car, pick it up at a designated place, use it, and return it to the original pick-up location. While two-way trip service requires customers to return a car to the original location, one-way trip service (such as car2go [4]) allows customers to drop off a car at another location near the destination, but still use only designated places for pick up and return.

Autonomous Vehicles (AVs) are expected to spark a revolution in transportation systems during the next half-century, offering a safe and low-stress transportation solution for customers [5]. The present study claims that Autonomous Electric Vehicle (AEV) sharing, which integrates autonomous and electric vehicle technologies, can result in a more sustainable and marketable car sharing service than traditional ones such as Zipcar and car2go.

An AEV as defined in this study follows five steps: A customer (i) becomes a member; (ii) enters location using a smart phone app and receives a wait time for a car; (iii) has car arrive in full-autonomous driving mode; (iv) drives car with no autonomous driving mode; and (v) leaves car at the destination. The car then travels to the next customer (in full-autonomous driving mode).

The chief benefit of this sharing service to customers is helping to avoid the hassle of pick-ups and returns. From a customer’s perspective, the AEV sharing service is the intersection of traditional car sharing services and call taxi (like Uber [6]) services, integrating the benefits of each.

From a service provider’s perspective, the challenge is that the AEV sharing service requires an optimal fleet assignment strategy to match AEVs with customers, while minimizing wait time of consumers and accounting for the AEVs’ charging schedule. For example, once a customer requests a ride, the optimal AEV should be selected among the whole fleet (i.e., among idle cars, in-service cars, and in-charging cars); after the trip, the AEV goes to either a charging station or to the next customer, or waits for the next trip at its current location. This fleet assignment process is depicted in Fig. 1. Besides fleet assignment, a service provider must also decide the number of AEVs needed, the service fee, and the number and location of charging stations. For AEVs specifically designed for this service, vehicle design variables must be also included.

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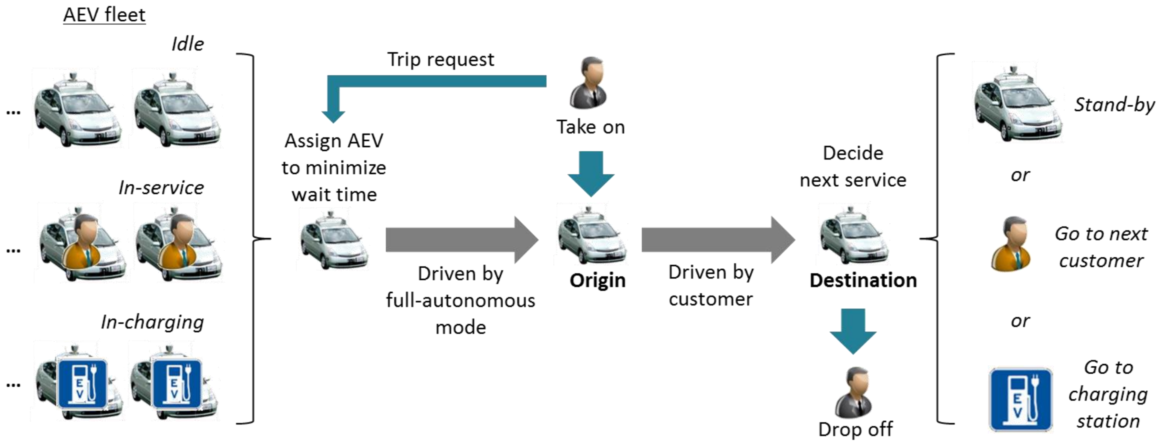

Figure 1. AEV-SHARING SYSTEM WORKING PROCESS

Previous studies have modeled fleet assignment and cost for AV-sharing services [7, 8] to calculate wait time, trip miles, fleet usage, and operating cost, given fleet size and trip request data (i.e., request times, origins, and destinations of customers). These studies considered gasoline vehicles rather than EVs. If an EV fleet is used for a sharing service, a service provider should consider battery charging schedules based on vehicle driving range, charging time, and charging station locations, because charging schedules affect the wait time of consumers and the wrong charging schedule can cause the vehicle run out of battery power. Further, consumer demand prediction (trip requests) was not modeled in these studies. Trip requests prediction is among the most important inputs of the fleet assignment simulation model and can be estimated via a consumer preference model with respect to wait time, service fee, etc. Finally, previous studies did not examine marketability (profitability) of such services, nor how different market scenarios may affect system decisions.

Design for Market System (DMS) research aims to integrate marketing, engineering, manufacturing, operations, and policy considerations to identify optimal design decisions [9-11]. This framework fits well the AEV sharing system design problem and is adopted in this paper, integrating four sub-system models (fleet assignment, charging station location, AEV design, and service demand) to make system-level decisions. Available models quantifying the relationship between EV design and charging station design (Kang [12,13]) are incorporated in the framework. .

The remainder of the paper is organized as follows. Section 2 introduces the AEV-sharing system design optimization framework and associated models. Section 3 presents optimization results for a study implementing such a service in Ann Arbor, Michigan. Section 4 summarizes conclusions and limitations.

2. SYSTEM DESIGN FRAMEWORK

The design framework consists of four subsystem models and integrates them to a system-level profit-optimization problem as shown in Fig. 2. The subsystem models are fleet assignment (Operations 1), charging station location (Operations 2), AEV design (Engineering), and service demand (Marketing). Red-highlighted variables indicate system-level decision variables. Other variables are linking responses of each model as summarized in Table 1.

The system-level objective is to maximize operating profit where: Operating profit = operating revenue – operating cost = (revenue from memberships + revenue from actual usage of the system) – (fleet operating cost + charging station operating cost + fleet ownership cost).

The decision variables for system-level optimization are AEV fleet size, number of charging stations, electric powertrain design, membership fee, and driving rate. The fleet assignment subsystem determines the optimal AEV assignment and charging schedules; and the charging station location subsystem determines the optimal charging station locations.

Bound constraints for all decision variables are imposed and tracked for possible activity at the optimum. Engineering requirements on the AEV performance are placed as inequality constraints for service feasibility (see Section 2.3).

Model parameters are selected to match the City of Ann Arbor, Michigan. Further details on the individual models are provided in the following sections. Throughout the ensuing analysis we assume that the AEV-sharing service operator owns the charging stations and the AEV fleet, so that all decisions are made simultaneously. This single owner case can be extended to a cooperation case with multiple stakeholders as shown in Kang [13].

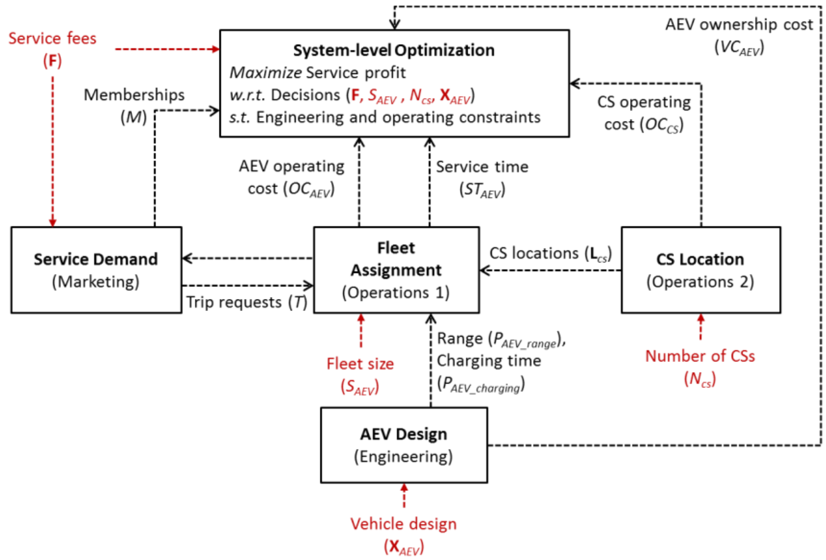

Figure 2. SYSTEM DESIGN FRAMEWORK

Table 1. OBJECTIVES AND VARIABLES OF MODELS

Model	System-level optimization	Fleet assignment (Operations 1)	Charging Station (CS) location (Operations 2)	AEV design (Engineering)	Service demand (Marketing)
Modeling purpose	Integration of subsystems	Optimal AEV assignment and charging scheduling	Optimal CS locating	City-driving simulation and feasibility check	Predict service demand
Objective	Maximize operating profit	Minimize wait time	Minimize distance between AEVs and CSs	-	-
System-level decisions	All system-level decision	AEV fleet size	Number of CSs	AEV design (Battery design, Motor design, and Gear ratio)	Service fees (Membership fee and Driving rate)
Local decisions	-	Fleet assignment and charging schedules	CS locations	-	-
Linking responses to other models	-	Wait time (*to Marketing*) Service time (*to System-level optimization*) AEV fleet operating cost (*to System-level optimization*)	CS locations (*to Operations 1*) CS operating cost (*to System-level optimization*)	Range (*to Operations 1*) Charging time (*to Operations 1*) AEV ownership cost (*to System-level optimization*)	Number of trip requests (*to Operations 1*) Number of memberships (*to System-level optimization*)

The system-level optimization problem is stated as follows.

$$\max_{\bar{\mathbf{X}}} \Pi = (F_M \times M + F_R \times ST_{AEV}) - (VC_{AEV} + OC_{AEV} + OC_{CS}) \quad (1)$$

with respect to

$$\bar{\mathbf{X}} = [\mathbf{F}, S_{AEV}, N_{CS}, \mathbf{X}_{AEV}] \quad (2)$$

subject to

$$lb \le \bar{\mathbf{X}} \le ub \quad (3)$$
$$\mathbf{g}_{AEV}(\mathbf{P}_{AEV}) \le \mathbf{0}$$

where

$$\mathbf{F} = [F_M, F_R] \quad (4)$$
$$\mathbf{X}_{AEV} = [\mathbf{B}_{AEV}, \mathbf{M}_{AEV}, G_{AEV}]$$
$$\mathbf{P}_{AEV} = [P_{AEV_{range}}, P_{AEV_{charging}}, P_{AEV_{speed}}, P_{AEV_{accel}}]$$
$$[W, ST_{AEV}, OC_{AEV}]$$

$$= f_{assign}\left(S_{AEV}, \mathbf{L}_{CS}, T, P_{AEV_{range}}, P_{AEV_{charging}}\right) \quad (5)$$
$$[\mathbf{L}_{CS}, OC_{CS}] = f_{CS}(N_{CS})$$
$$[\mathbf{P}_{AEV}, VC_{AEV}] = f_{AEV}(\mathbf{X}_{AEV})$$
$$T = f_{demand}(\mathbf{F}, W)$$

The system-level objective Eq. (1) is to maximize operating profit Π; Eq. (2) is the system-level decision variables $\bar{\mathbf{X}}$ for the four subsystems; Constraints in Eq. (3) includes bound constraints on the decision variables and inequality constraints $\mathbf{g}_{AEV}$ on the AEV performances $\mathbf{P}_{AEV}$; the decisions variables and responses are defined in Eq. (4); and the four subsystem models, f_{assign}, f_{CS}, f_{AEV}, and f_{demand} in Eq.(5) indicate the fleet assignment model, charging station location model, AEV design model, and service demand model, respectively. The nomenclature for the equations above is described in the last section of this paper.

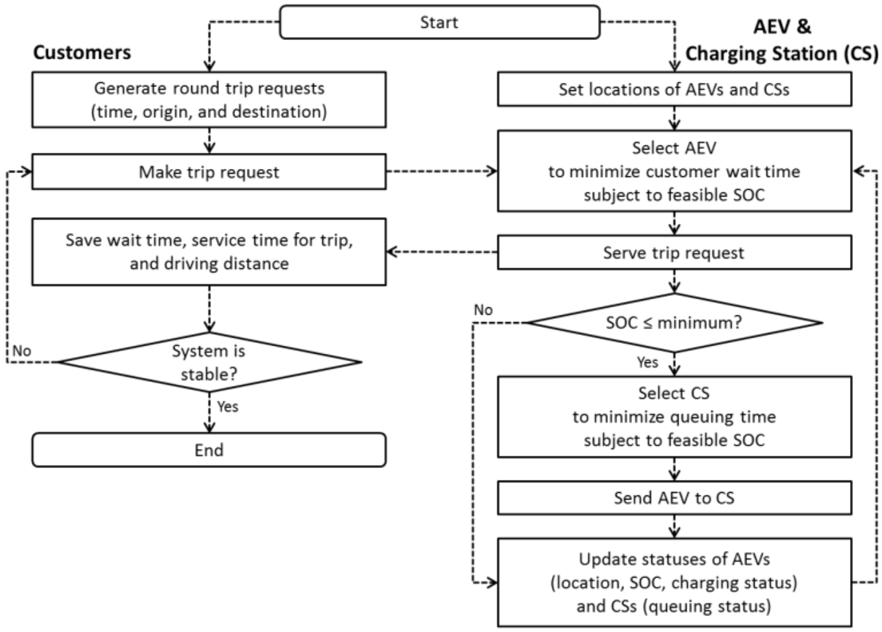

Figure 3. AEV FLEET ASSIGNMENT SIMULATION MODEL

2.1. Fleet Assignment Model (Operations 1)

The system-level fleet assignment problem links all subsystem problems. Inputs from subsystems are charging station locations from Operations Model 2 (Section 2.2), AEV range and charging time from the engineering model (Section 2.3), and trip requests from the marketing model (Section 2.4). Outputs are wait time, total service time, and AEV fleet operating cost, which are also used as inputs for other models, Figure 1. Every output is an optimal response resulting from solving the local optimization problem to minimize wait time with respect to fleet assignments and charging schedules.

We assume that there is a central information system that gathers all real-time information such as location and SOC (state of charge) of AEVs and queuing status of charging stations, and then directs the AEVs. The central information system will work as follows:

(1) A trip is requested from a customer by the smart phone app. A customer inputs his/her origin and destination.

(2) The system calculates wait times of all deployed AEVs. There are three AEV states: Idle AEVs that can come to the customer directly from the current location; in-service AEVs that can come after finishing current service; and in-charging AEVs that can come after finishing charging battery.

(3) The system assigns the AEV to minimize wait time subject to feasible SOC, which means the AEV should have enough SOC to go to the nearest charging station without running out of battery after finishing the service.

(4) The assigned AEV goes to the customer in fully-autonomous driving mode, the customer drives it by him/herself to the destination and leaves it there.

(5) The AEV records and transmits total service time to the central information system. The customer can check monthly statement and pay his/her driving rates online.

(6) The central information system checks the current SOC of each AEV. If the SOC reaches a lower bound, the system checks queuing time and distance to charging stations, and selects the charging station that makes the vehicle ready for service most quickly. If the vehicle is selected for the next customer, it goes there directly. If it is not selected and has higher SOC than the lower bound, it goes on stand-by at the current location.

To simulate the scenario above, we generated trip request inputs (i.e., time, origin, and destination) using Monte Carlo simulation. For origins and destinations, we generate the set of coordinates on a square of 11×11 miles representing the city of Ann Arbor. We assume that a customer desires a round-way trip but doesn't need to hold the AEV at the destination, unlike traditional car sharing services. Instead, the customer requests another AEV when ready to return, like taxi services. For trip request times, we sample times using the distribution of person-trips per day from a US government report [14].

Driving distances are calculated from the Euclidean distance between origins and destinations multiplied by a proportional parameter, α [7]. In the study we set $\alpha = 1.4$. To estimate driving time, we use the average driving velocity 21.2 mph of the FTP-75 driving cycle, representing city driving in the U.S. This driving cycle is also used in the engineering model to simulate vehicle performance, including battery consumptions, as shown in Fig. 7.

Given input data (i.e., fleet size, charging station locations, vehicle range, charging time, and trip requests), we set initial vehicle locations randomly with 80% SOC, and execute the simulation depicted in Fig. 3. The simulation is for outputs over a 24-hour operation period. However, the model is run until every vehicle recharges its batteries more than two times, beyond 24 hours. This is because, while wait times are short when all vehicles have enough SOC early on, wait times increase when vehicles start to recharge their batteries. According to pilot simulation experiments, when every vehicle recharges at least two times, wait times become stable. We used outputs of the last 24 hours after every vehicle recharges two times.

Due to the stochastic nature of the simulation, we run the simulation 10 times for each individual set of inputs and average them. Total service time is used to calculate service income, and total vehicle driving distance is used to calculate AEV operating cost.

A meta-model was created from this simulation to facilitate system optimization. We run simulations for 10,000 inputs generated using the Latin hypercube sampling routine in Matlab [15]. The results show that fleet size and trip requests affect wait time most strongly under predetermined lower and upper bounds of inputs. As long as fleet size is sufficiently large to cover the trip requests, other factors such as vehicle range, charging time, and charging stations number do not affect wait time much. When fleet size is not large enough, the wait time becomes sensitive to other factors as well.

Figure 4 shows a plot of the 10,000 output points with the x-axis being the number of vehicles per trip request and the y-axis being wait time. The ratio "vehicles per trip" request affects wait time substantially. Wait time rises sharply when the ratio becomes smaller than around 0.1. Different wait times for the same ratio occur due to differences in vehicle range, charging time, and number of charging stations. Charging time does not exert a strong effect on wait time because the rate of change in charging time is limited due to the engineering constraints used here. Based on these findings, two meta-models were created for a vehicles-per-trip-request ratio greater than or equal to 0.1 and less than 0.1, using the Matlab Neural Networks software [15].

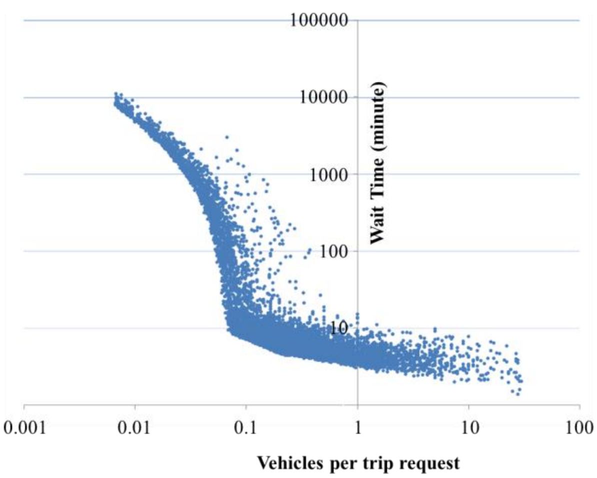

Figure 4. WAIT TIME SIMULATION RESULTS

The AEV operating cost model includes insurance, tax, maintenance, and overhead costs by adopting the cost models in [7]: Insurance cost = \$3,000×years×vehicles; tax = \$600×years×vehicles; maintenance cost = \$0.05×driving miles; and overhead cost = \$1000×years×vehicles. Net Present Value (NPV) with 10% discount rate is used for all cost calculations with ten years of business operations assumed.

2.2. Charging Station Location Model (Operations 2)

The charging station location model from Kang [13] with the *p*-median model [16] is used to determine optimal station locations in Ann Arbor. The locations of *p*-stations are selected to minimize the average distance between AEV locations and the closest *p*-stations, where *p* indicates the number of stations. Since an AEV fleet needs space for charging but also for maintenance, the 15 candidate locations (A to O) were selected among the existing public parking lots in Ann Arbor as shown in Fig. 5.

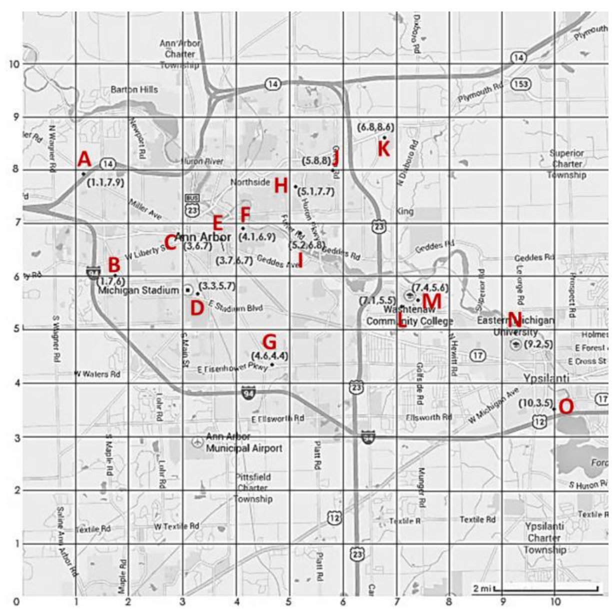

Figure 5. CANDIDATES OF CHARGING STATION LOCATIONS [13]

The best combination of charging stations given the number of stations available is computed assuming that AEVs are deployed uniformly in Ann Arbor (11×11 miles). The optimal locations are determined prior to system-level optimization, Table 2. This look-up table is then used in system optimization to find the optimal number of stations.

We assumed Direct Current (DC) fast-charging stations with a single charger. The charging cost includes installment, maintenance, and electricity costs. Fast DC charger cost models are adopted from [17]: Installment cost = \$75,000×chargers; maintenance cost = \$5,500×chargers. For electricity cost, 10.28 cents per kWh is used based on average retail price for transportation in the U.S. [18]. All costs are calculated over ten years with discount rate of 10%.

Table 2. OPTIMAL CHARGING STATION LOCATIONS [13]

# of CSs	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	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●

2.3. AEV Design Model (Engineering)

The AEV design simulation model adopted from Kang [12] consists of driver, control unit, motor torque control, battery, inverter, motor, and driving simulation models as shown Fig. 6.

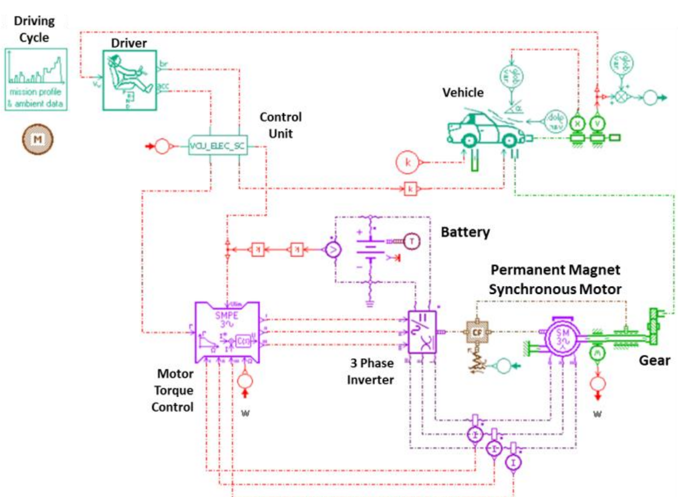

Figure 6. ENGINEERING SIMULATION MODEL [12]

The model was built using the AMESim software [19]. Here we focus on the lithium-ion battery, permanent magnet synchronous motor, and gearing design. Design variables and boundary constraints are shown in Table 3.

This vehicle engineering performance is used to evaluate the inequality constraints in system-level optimization. These constraints ensure highway driving and service feasibility: Range (P_{AEV_range}) $\geq$ 50miles; Top speed (P_{AEV_speed}) $\geq$ 70mph; and 0 to 60 (P_{AEV_accel}) $\leq$ 30sec.

Range (P_{AEV_range}) and charging time ($P_{AEV\_charging}$), as outputs of the simulation, are used in the fleet assignment model (Section 2.1) as inputs. Since AEV sharing is a city-based service, we used the FTP-75 driving cycle in Fig. 7.

Table 3. ENGINEERING DESIGN VARIABLES

System	Design variables	Lower bound	Upper bound
Battery ($\mathbf{B}_{AEV}$)	Number of cells in series in on branch	80	200
	Number of branches in parallel	1	4
Motor ($\mathbf{M}_{AEV}$)	Stator inductance of the d-axis	1.62mH	3.42mH
	Stator inductance of the q-axis	1.98mH	4.18mH
	Stator resistance	0.001Ω	0.1Ω
	Number of pole pairs	1	4
Gear (G_{AEV})	Gear ratio	2	12

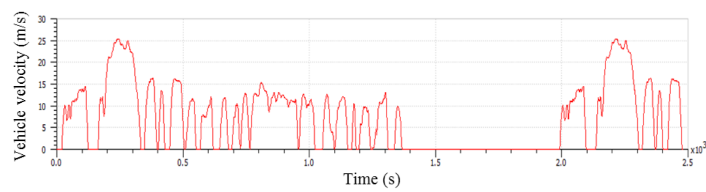

Figure 7. FTP-75 DRIVING CYCLE [19]

Vehicle and battery parameter values are based on the Nissan Leaf [20,21]. Charging time is estimated based on battery capacity using linear scaling and assuming it takes 30 minutes for a DC fast charging station to recharge 80% of 24kWh battery. The meta-model for system-level optimization was built using the Matlab Neural Networks package [15]. Detailed analytical equations for each design component can be found in [12].

To estimate EV cost, we used battery pack and a motor costs as variable costs, all other costs assumed fixed at a total of \$6,000. The autonomous driving module cost is assumed to be \$2,500 following [7]. Battery cost was assumed at \$500/kWh following [12]. Motor cost was computed from [22]: Motor cost (\$) = 16 × motor power (kW) + 385.

2.4. Service Demand Model (Marketing)

We used Hierarchical Bayesian (HB) choice-based conjoint [25, 26] to build a heterogeneous service demand model. The service demand model predicts the number of memberships and the number of trip requests using the service attributes: Pick-up and return type (i.e., autonomous or self); time required for pick-up and return; membership fee; and driving rates. Attribute levels are based on existing car sharing services [3, 4, 23] as shown in Table 4.

The individual-level utility v_{ij} is defined as

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} z_{jkl}, \qquad (6)$$

where z_{jkl} are binary dummy variables representing alternative j possesses attribute k at level l, and β_{ikl} are the part-worths of attribute k at level l for individual i [24].

In HB conjoint, it is assumed that an individual's part-worths, $\boldsymbol{\beta}_i$, have a multivariate normal distribution, $\boldsymbol{\beta}_i \sim N(\theta, \boldsymbol{\Lambda})$, where θ is a vector of means of the distribution of individuals and **Λ** is the covariance matrix of that distribution.

Table 4. ATTRIBUTES LEVELS AND IMPORTANCES

Attributes	Unit	Level 1	Level 2	Level 3	Level 4	Importance
Pick-up and Return Type		Self	Autonomous			14.7%
Time Required for Pick-up and Return	minutes	5	10	20	30	13.5%
Membership fee	\$/month	2	5	7	10	45.7%
Driving rates	\$/10 minutes	1	1.5	2	2.5	26.1%

The choice probability is calculated using the logit model

$$P_{ij} = \frac{e^{v_j}}{\sum_{j' \in \mathbf{J}} e^{v_{j'}}}, \tag{7}$$

where P_{ij} indicates the probability individual i chooses option j from a set of alternatives **J**. Then we draw an individual's part-worths using Markov chain Monte Carlo (MCMC). For the case study, we used every tenth draw from the last 50,000 (of 100,000 total). After getting discrete part-worth coefficients, a natural cubic spline is used to interpolate the intermediate values of attributes, and create individual-level utility models with respect to continuous attributes. Average market demand q_j can be forecast by the choice probabilities P_{ij} and market potential s:

$$q_j = \frac{1}{I}\sum_{i=1}^{I} sP_{ij}. \tag{8}$$

More detailed description of this demand model can be found in [12, 27]. Note that, in system-level optimization, we use an individual-level market demand $(q_{ij} = sP_{ij})$ for calculating profit, and then use the average profit for all individual market scenarios as objective. Therefore, the optimization result can account for a heterogeneous market.

For the study we projected the potential market size of car sharing membership in Ann Arbor to be 455 based on population ratio (i.e., Ann Arbor population / U.S. population) and U.S. market size with 1.2 million car sharing members as of January 2014 [2]. The number of daily trip requests is estimated from the number of AEV service memberships and frequency of use, assuming that members use a car sharing service 3.34 times per month [1]: Potential daily trip requests = car sharing memberships × 3.34 / 30days. As a market competitor we used the Zipcar service in Ann Arbor.

Consumer choice data are gathered using a choice-based conjoint survey from 245 subjects who live in Ann Arbor or similar sized cities in the U.S. Subjects were hired through the survey company ClearVoice Research [28]. We eliminated subjects who chose the "None" option for more than half of all choice questions, and thus used results from 178 subjects as potential car sharing members. We then built 178 individual-level utility models. The importance of attributes is shown in Table 4, which presents average values of importance for each individual-level model.

The subjects consisted of 44% males and 56% females; 4% were 18 to 24 years of age, 21% were 25 to 34 years of age, 21% were 35 to 44 years of age, 22% were 45 to 54 years of age, 19% were 55 to 64 years of age, and 13% were more than 65 years of age.

The following section will discuss the optimal decisions that maximize service profit using the models in Section 2.

3. OPTIMIZATION RESULTS

We used the Matlab Genetic Algorithm (GA) [15] to solve the mixed integer optimization problem of Eq. (1). We examined three different potential market scenarios: Current market of 455 members, then doubled and tripled the market size. The latter scenarios were specified since we have no reliable estimate of market growth.

Tables 5 and 6 show optimal decisions and market responses, respectively. To calculate profit, we used 178 heterogeneous consumer preference models, so that responses are also heterogeneous. The values in Table 6 present the average values of 178 responses.

Table 5. OPTIMAL DECISION VALUES

Model	Variable	Current market	Doubled market	Tripled market
AEV design (Engineering)	Number of cells in series in on branch	192	104	101
	Number of branches in parallel	1	2	1
	Stator inductance of the d-axis	2.97mH	2.65mH	2.80mH
	Stator inductance of the q-axis	3.64mH	3.24mH	3.42mH
	Stator resistance	0.052Ω	0.038Ω	0.050Ω
	Number of pole pairs	4	2	3
	Gear ratio	4.93	5.17	5.17
Fleet assignment (Operation 1)	AEV fleet size	10	12	19
Charging station locations (Operation 2)	Number of charging stations	1	1	3
	Locations of charging stations	I	I	D, K, N
Service demand (Marketing)	Membership fee	\$1.8	\$1.6	\$1.7
	Driving rate	\$2.5	\$2.5	\$2.5

The results show that the optimal market share of AEV-sharing service is not affected by market size. The driving rate (\$/10min) at the optimum hits its upper bound in all scenarios, so setting this bound would merit further attention. The membership fee does not change much with market size but other optimal values adjust to give the same market share.

Optimized fleet size, vehicle range, and number of charging stations resulted in short wait time for all three scenarios. For the triple-sized market, optimal fleet size and number of charging stations increased significantly to cover the increased service demand. However, optimal vehicle range (battery capacity) decreased, resulting in lower vehicle ownership cost. This indicates that trading off engineering decisions (vehicle range) and operations decision (fleet size and number of charging stations) may vary with market size.

The optimal membership per vehicle for an AEV fleet is lower than the one for current car-sharing service, which averages 72:1 as of January 2014 in the US. Therefore the AEV fleet will be larger than the traditional service.

Table 6. RESPONSES OF MARKET SCENARIOS

		Current market	Doubled market	Tripled market
Market response	Total profit	$11.05M	$22.5M	$34.2M
	Market share	71.5%	71.2%	72.3%
	Memberships	325	648	987
	Memberships per vehicle	32.5:1	54:1	51.9:1
	Round trip requests per day	36.5	72.8	110.4
AEV fleet operating	Wait time	7.6minute	8.0minute	4.9minute
	Fleet service distance per day	782miles	1,549miles	2,261miles
AEV attributes and specs	Range	148.2miles	150.0miles	76.7miles
	Top speed	105.5mph	86.5mph	83.6mph
	Acceleration (0to60)	13.4sec	24.5sec	24.0sec
	MPGe	206.6	192.9	204.0
	Battery capacity	24.1kWh	26.2kWh	12.7kWh
	Motor power	73.4kW	44.2kW	39.9kW
Cost	Fleet ownership (vehicle ownership)	$221K ($22,133)	$272K ($22,673)	$302K ($15,875)
	Insurance	$199K	$239K	$379K
	Tax	$40K	$48K	$76K
	Electricity	$25K	$54K	$75K
	AEV maintenance	$95K	$188K	$274K
	Overhead cost	$66K	$80K	$126K
	Charging station maintenance	$37K	$37K	$110K
	Charging station installment	$75K	$75K	$225K

4. CONCLUSION

Autonomous driving technology is expected to be deployed on a commercial scale within ten years, and electric powertrain technology already has been successfully launched in the market. Combining these two technologies will create car sharing service alternatives, including the AEV we studied here in terms of feasibility with respect to profit, operations, engineering, and marketing. Challenges for a new AEV sharing service system design are long battery charging times and low driving range, making the service potentially slow and even cause autonomous services terminations. The presented integrated decision framework for autonomous fleet assignment, charging station locating, and powertrain design can result in low wait time for customers and a stable service under different market simulations. Customer anxiety and discomfort with electric powertrains is reduced if AEVs recharge by themselves and come on time. Another concern is cost. In spite of the relatively large cost of AEV fleet and charging stations, the integrated analysis of the proposed AEV shows both high profit and market share compared to a traditional car-sharing service.

In future work, additional scenarios through further parametric studies and sensitivity analyses can explore the range of applicability of this study's results. Accounting for uncertainties and stochastic market responses is a further future refinement. Finally, analyzing the ramifications of system optimization results for individual domain decision makers could provide practical insights.

NOMENCLATURE

$\mathbf{B}_{AEV}$: battery design variables
f_{AEV} : AEV design model (Engineering)
f_{assign}: fleet assignment model (Operations 1)
f_{CS} : charging station (CS) location model (Operations 2)
f_{demand} : service demand model (Marketing)
$\mathbf{F}$: service fees
F_M : membership fee
F_R : driving rate
G_{AEV} : gear ratio
$\mathbf{L}_{CS}$: CS locations
$\mathbf{M}_{AEV}$: motor design variables
M : number of memberships
N_{CS} : Number of CSs
OC_{AEV} : AEV fleet operating cost
OC_{CS} : CS operating cost
$\mathbf{P}_{AEV}$: AEV performance
P_{AEV_range} : range
$P_{AEV\_charging}$: charging time
P_{AEV_speed} : top speed
P_{AEV_accel} : acceleration
S_{AEV} : AEV fleet size
ST_{AEV} : service time
T : number of trip requests
VC_{AEV} : AEV ownership cost
W : wait time
$\mathbf{X}_{AEV}$: AEV design variables
Π: profit

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