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Addressing human factors in electric vehicle system design: Building an integrated computational human–electric vehicle framework

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HIGHLIGHTS

► Propose a new human driver-centered framework in electric vehicle design.
► Design a new cost-effective driving simulator-based EV battery test platform.
► Analyze and optimize the effects of driver behavior on battery lifetime using ICHEV.

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ABSTRACT

The electric vehicle (EV) has been developing rapidly and predicting the lifetime of Li-ion batteries in EVs has become an important issue. Characteristics of human drivers and the battery configuration interact and both play important roles in determining EV battery lifetime. Moreover, due to the relatively high cost of real EVs and long testing time for battery life of EVs, it is important to integrate the human driver and EV battery into one framework and implement it in a driving simulator test-bed. To address this problem, the current work proposes the first integrated computational human–electric vehicle framework (ICHEV) and implemented in a STISIM driving simulator. ICHEV can be used to: 1) Analyze the effects of driver differences (including driver characteristics, charging strategy, and driving schedule) and battery configuration on battery lifetime in saving real EV test cost and time; 2) Predict the battery lifetime given the driver characteristics, driving schedule, and battery configuration; and 3) Obtain the optimal battery configuration, the optimal driving patterns and charging strategy for the purpose of maximal battery lifetime. According to the ICHEV, software was developed and further applications of the ICHEV were also discussed.

1. Introduction

Electric Vehicle (EV) technologies have received great attention due to the potential contributions to reducing carbon dioxide emissions and energy consumption [1]. EVs differ from fossil fuel-powered vehicles in that the electricity they consume can be generated from a wide range of energy, including not only fossil fuels and nuclear power, but also renewable power from hydraulic, wind, solar, geothermal, and tidal sources. EVs release almost no carbon dioxide and air pollutants.

The advancement of EV technologies greatly depends on the development of battery technologies. Lithium-ion batteries, which have high-energy storage and power density and competitive cost, have become the first choice as the power source by major EV manufacturers [2]. Although a lot of research has been conducted for lithium-ion EV batteries and various performance characteristics have been explored, the Li-ion batteries have not yet been able to simultaneously meet the intensive energy demands, long life cycle, and low cost which are unique to vehicular-propulsion applications [3]. Additionally, battery life in service/usage is another major concern when consumers consider buying EVs [4]. For example, General Motors (GM) Chevrolet Volt Extended-Range EV is priced at $40,280 before federal tax credit. The heart of Volt is the T-shaped lithium-ion battery pack which costs approximately $10,000 each [5]. If the batteries have a shorter life cycle than the vehicle itself and need replacement every few years, the high initial EV cost, battery replacement cost, and charging cost can easily surpass the cost of a conventional internal combustion engine vehicle running on gas when distributed over the life cycle of the vehicle. Thus, improvement in battery life cycle and reliability is undoubtedly essential before attempting to push potential buyers to take the plunge.

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The majority of available literature on EV batteries is concerned with problems such as Li-ion cell electrochemistry and new materials [6,7], battery dynamics and simulation [8,9], battery management systems and cell charging/discharging equalization [8], and environmental impact and sustainability [10,11]. However, the effects of human factors on the performance of the batteries have been largely neglected. Only a few studies considered it but simplified driver as a minor module in their systems [1,12]. For example, Musardo et al. (2005) used a Driver Module comparing the desired vehicle speed with the actual velocity and calculating the accelerator or brake commands through a PI controller [1]. Bowles et al. (2000) simulated the vehicle's performance with a Driver model to represent the power demand of the driver [12]. Very few of them considered the role of the human being (the real manipulator of the EV) in the loop of the EV framework.

Even though real EVs have been used as test-beds for EV batteries, they are relatively expensive to run the tests and take a long time to obtain experimental data from. The data collection involving fifteen EVs lasted two years in Liaw and Dubarry's work [13]. Researchers at GM conducted a large scale experiment spending more than $30,000 for each EV. Even with this large investment, however, GM could hardly sustain the real driving experiment of the EVs for more than one year. Moreover, since EV battery lifetime is usually more than 36 months, it will be quite time-consuming to obtain the EV battery lifetime data using a real EV. Due to the high cost of real EVs and EV batteries, a simulated driving platform integrated with an EV battery simulation module can be very cost-effective (a desktop version usually cost less than $2500, e.g., STISIM®) and less time (less than 1 h) without any cost of gas or battery power.

Moreover, drivers with different personal characteristics (i.e., personality, decision making reference (DMR) of speed choice) exhibit different driving patterns (i.e., speed and acceleration/deceleration [14];) with their different impacts on EV battery. For example, an increase of driving speed leads to elevated operating temperature and produces higher discharging power load on EV batteries [9]. Also, the individual driver exhibits different charging strategies, which affect the battery lifetime. If a driver chooses to charge the battery when the residual energy is enough for a daily commute (conservative charging strategy), the battery is charged more frequently, which increases the number of charging–discharging cycles [15]. Several empirical studies of driving patterns or driver profiles (e.g., driving distance and driving speed) and charging strategy were conducted [16–18]. In human factors related to transportation, driving simulators (e.g., STISIM® and Drive Safety®) are widely used to simulate various road types and traffic situations to study driver behavior and their individual differences; however, few studies integrate an EV battery model or simulation module into a driving simulator.

The objective of this study was to develop an integrated computational human–electric vehicle framework (ICHEV) considering both driver behavior and EV battery. ICHEV has been implemented in a driving simulator (STISIM®) as a cost-effective test-bed. The human driver experiment was conducted using the integrated test-bed and ICHEV can be used to: 1) Predict the battery lifetime given the fixed driver characteristics, driving schedule, and battery configuration; 2) Generate the optimal battery configuration to maximize the battery life cycle; 3) Provide the individual driver's optimal driving patterns and charging strategy for the purpose of maximal battery lifetime. According to the ICHEV, software was also developed to facilitate the achievement of these three objectives.

The remainder of this paper was organized as follows. Section 2 described the ICHEV and each element in the framework. Section 3 introduced the methods to optimize the battery configuration or driving patterns and charging strategy. Section 4 described the details of an experimental study to validate the ICHEV and examine the factors (both human and engineering) that have significant

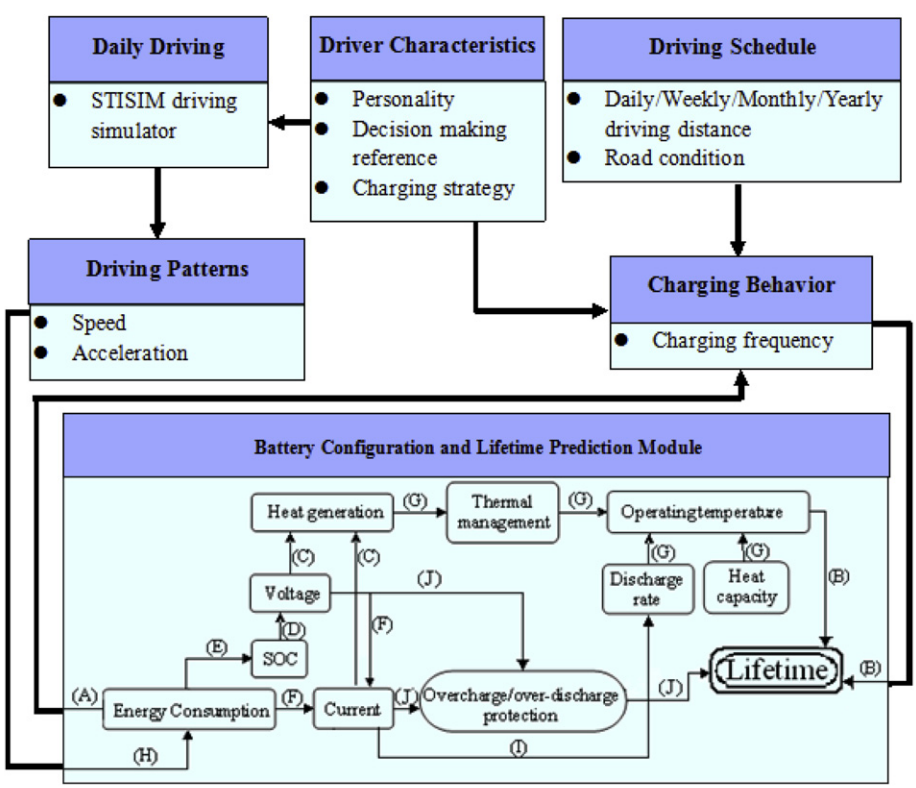

Fig. 1. The integrated human–electric vehicle framework (ICHEV).

effects on battery lifetime. According to the ICHEV, software was developed and presented in Section 5. The conclusion and discussion of future work are presented in Section 6.

2. The integrated computational human–electric vehicle framework

An integrated computational human–electric vehicle framework was developed to take both human and engineering factors into account on the EV platform. The basic architecture of the ICHEV consisted of five major elements: driver characteristics, driving patterns, driving schedule, battery charging strategy, and EV battery simulation and lifetime prediction module. As shown in Fig. 1, driving patterns (See Section 2.1 in details), driver characteristics (See Section 2.2 in details), and driving schedule (See Section 2.3 in details) interacted to determine the battery charging profile module (See Section 2.4 in details). Driving patterns, charging strategy, and the battery configuration interacted to predict the lifetime of the plug-in EV battery (See Section 2.5 in details).

Moreover, ICHEV has been implemented in a desktop version of a driving simulator (STISIM®) and with another computer. When a driver operates the driving simulator, the simulator collects his or her driving behavior in real time (e.g., speed and acceleration) and sends this information to an EV battery simulation module installed on the other computer. The battery simulation module then sends battery status information to the driver via the on-board display (See Fig. 2).

2.1. Driving patterns module

The driving patterns module considered two vehicle variables as model inputs: speed (v) and acceleration (a). In this work, these driving variables were collected from the driving simulator that was connected to the battery simulation and lifetime prediction module (See Fig. 2). More specifically, the driving simulator collected driving speed and acceleration at each time interval, recorded as inputs in the battery simulation module. Based on these driving data, the battery simulation module calculated the energy consumption spent driving and the residual energy. The information regarding residual energy was sent back to the driving simulator and displayed on the bottom right corner of the dashboard.

2.2. Driver characteristics module

The Driver characteristics module consisted of three individual factors: personality, decision making reference (DMR), and charging strategy. Personality refers the impulsiveness of a driver. Decision making reference (DMR) refers to the magnitude of speed if a driver tends to exceed the posted speed limit. Zhao and Wu (2011) found that drivers with different personalities and decision making references (DMR) have different behaviors of speed controls [14], which lead to different energy consumption spent driving [9]. In this paper, charging strategy refers to the percentage of the battery residual energy after the daily commute at which a driver decides to charge the battery. If a driver charges the battery at a higher percentage of the residual energy, he or she might charge the battery more often, which eventually shortens the battery lifetime [19]. Thus, a driver's charging strategy determines the charging frequency, which directly influences the battery lifetime.

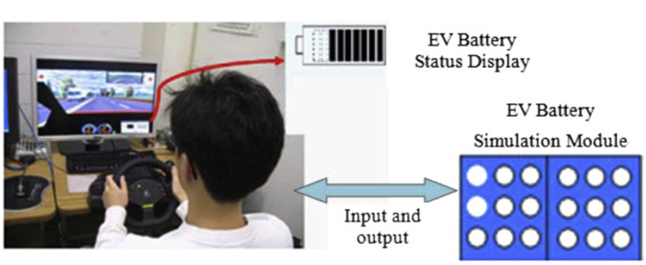

Fig. 2. Implementation of ICHEV in STISIM® driving simulator with EV battery simulation module.

2.3. Driving schedule module

The Driving schedule module provided a driver's daily driving distances on each type of road as model inputs. The daily driving distance was calculated based on a driver's daily commute distance on weekdays, driving activities (e.g., shopping) on the weekend, and driving plans on holiday or vacation. Road type consisted of two conditions: urban and highway. Accordingly, the average daily energy consumption (E) was the sum of the energy consumed on urban road (E_u) and highway (E_h) (See Equation (1)).

$$E = E_\mathrm{u} + E_\mathrm{h} = \frac{D_\mathrm{u}}{d_\mathrm{u}} e_\mathrm{u} + \frac{D_\mathrm{h}}{d_\mathrm{h}} e_\mathrm{h} \tag{1}$$

Where, D_u and D_h are the real driving distances on the urban road and highway. d_u and d_h are the driving distances on the urban road and highway in a simulated driving task. e_u and e_h are the energy consumptions on the urban road and highway which are collected from the driving simulator.

2.4. Battery charging profile module

Driving patterns, driver characteristics, and driving schedule interacted to determine the battery charging frequency. As shown in Equation (2), the battery charging frequency (f) was equal to the ratio of the average daily energy consumption to the average battery energy consumption within one charging interval.

$$f = \frac{E}{(1-q)\cdot Q} \tag{2}$$

Where q was the average percentage of the battery residual energy leading the driver charging the battery, Q is the battery capacity.

2.5. Battery simulation and lifetime prediction module

As illustrated in Fig. 1, both human and engineering factors affected the EV battery lifetime. The most direct factors were the operation temperature (T), charging frequency, the average daily energy consumption, and the battery capacity when it is manufactured (Q_0) (See Equation (3)). The operation temperature is the temperature at which an EV battery operates. It was affected by the initial temperature, open circuit voltage, operation voltage, the current of the battery, the heat capacity of the battery, and the heat management module. The open circuit voltage, operation voltage, and current of the battery are affected by State of Charge (SOC). All connections (from A to J) proposed in the battery simulation and lifetime prediction module, equations, parameter settings, and references were summarized in Appendix A.

$$\mathrm{LT} = \frac{167.583 - 1.264\cdot T - 100\cdot E/Q_0}{0.097\cdot f} \tag{3}$$

According to the ICHEV, in the following section, we provided the algorithms to optimize the battery configuration, driving patterns, and charging frequency for the maximal battery lifetime.

3. Optimization of the battery configuration, driving patterns, and charging strategy

The sequential quadratic programming (SQP) was used to optimize the battery configuration for the purpose of maximal battery lifetime given a driver's driving patterns, driver characteristics, and driving schedule [20,21]. The SQP was also performed to optimize the individual driver's driving patterns and charging strategy for the same purpose based on the fixed battery configuration. A General Problem (GP) was described as follows (where x is the vector of length n design parameters, and $f(x)$ is the objective function[1]):

$$\min_x f(x) = \min_x \frac{1.264\cdot T + 100\cdot E/Q_0 - 167.583}{0.097\cdot f} \quad \text{Subject to} \quad \begin{cases} 80 \le N \le 320 \\ 720 \le C_p \le 1020 \\ 0 \le \Delta\text{heat} \le 380 \end{cases} \tag{4}$$

4. An experimental study of ICHEV

An experiment with real human drivers was conducted with the new driving simulator test-platform. Driver characteristics, driving schedule, and charging strategy were obtained through questionnaires. Driving patterns were collected from a driving task close to real-world daily driving scenarios. From this experimental study, each participant's energy consumption in daily driving was obtained based on his/her driving schedule and driving patterns. Then, the predicted EV battery lifetime was calculated for each driver. Next, the effects of driver characteristics, driving schedule, and battery configuration on battery lifetime were analyzed. Finally, the optimal battery configuration, driving patterns, and charging strategy were obtained.

4.1. Participants

Twelve drivers (6 males, 6 females) ranging from age 26 to 50 ($M = 34.5$, $SD = 5.58$) took part in this study. The average driving experience was 4.76 years and average annual mileage was 9200 miles. All of them had valid drivers licenses, at least three years driving experience, and had driven within the past month.

4.2. Self-report measures

All participants were asked to complete a set of questionnaires after engaging in the driving task. The first questionnaire was designed to obtain each participant's demographic situation (such as age, gender, etc), driving history (such as estimated cumulative driving mileage, the year a drivers license was first issued, etc), and driving schedule (such as daily/weekly/monthly/yearly driving distance, road type, etc). Secondly, all participants were required to construct a subjective value matrix regarding their attitudes towards the cost and/or benefit of speeding, from which decision making references were obtained (For a detailed description of this questionnaire and decision making reference calculation (see Ref. [14,22])). Thirdly, a short form of the Revised Eysenck Personality Questionnaire (EPQR-S [23],) was used to divide all drivers into three categories: normal drivers (those characterized as E+ and N− or E− and N+, $n = 6$); impulsive drivers (those characterized as E+ and N+, $n = 3$); and non-impulsive drivers (those characterized as E− and N−, $n = 3$). Finally, at the end of each simulated trip, the driving simulator test-bed asked each participant if he or she would charge the battery under different charging conditions.[2] As shown in Fig. 3 and Fig. 2, the dashed bars indicate the energy consumption during the daily commute and the black bars indicate the residual energy after a driver's daily commute.

According to drivers' responses, the percentage of the battery residual energy after a driver's daily commute (q) was computed as follows:

$$q = \frac{\sum_{i=1}^{25} q_i \cdot h_i}{\sum_{i=1}^{25} h_i} \quad (h_i = 1 \text{ if the driver answers "Yes"; otherwise } h_i = 0) \tag{5}$$

4.3. Apparatus

A STISIM® driving simulator (STISIMDRIVE M100K) was used in the experiment (See Fig. 2). It includes a Logitech Momo® steering wheel with force feedback, a throttle pedal, and a brake pedal. The STISIM simulator was installed on a Dell Workstation (Precision 490, Dual Core Intel Xeon Processor 5130 2 GHz) with a 256 MB PCIe × 16 nVidia graphics card, Sound Blaster® X-Fi™ system, and Dell A225 Stereo System. Driving scenarios were presented on a 27-inch LCD with 1920 × 1200 pixel resolution.

4.4. Driving scenario and measurement

The Test Block simulated a 16-mile commute environment based on the average daily commute profile (the average one-way commute time in the United States is 26 min and commute distance is 16 miles) [16]. It consisted of 55% urban driving and 45% highway driving [24]. Therefore, the Test Block was divided into three sections: the first being 30% of driving on urban, the middle being 45% of driving on highway, and the last being 25% of driving on urban again. The speed limits ranged from 25 to 55 mph on the urban road and were set at 65 mph on the highway. Participants were instructed to follow the speed limit and adjust their speed as if they were driving a real vehicle on the road throughout the task.

Behavioral measures from the driving simulator Test Block were automatically collected: time elapsed (unit in second), speed (ft s^{-1}), acceleration (ft s^{-2}), and distance (feet). These experimental driving data were used to obtain the battery energy consumption.[3]

4.5. Results

4.5.1. Energy consumption and predicted battery lifetime

The battery energy consumption in the driving task was calculated based on participants' driving variables. The battery energy consumption in each participant's daily driving was then obtained using Equation (1) based on his/her own driving schedule.

[1] The optimal battery configuration was first generated for the average driver: heat capacity was 1020 (range = 700–1020 J kg^{-1} K^{-1} [27],), heat reduction was 380 (range = 0–380 W m^{-2} K [27],), and the number of cells in the battery pack was 320 (range = 80–320 [28,36–38],]) given $T_0 = 10$ °C.

[2] If the residual energy is less than the energy consumed per day, the driver has to charge the battery for the purpose of daily commute, which is not the charging strategy that we expect. Instead, we are interested in how a driver makes a decision on battery charging when the residual energy is no less than the daily energy consumption. As a result, there were 25 combinations that met the requirements.

[3] These driving variables were used to calculate the energy consumption of the battery in the driving task in accordance with Peterson et al. (2010)'s work [9] so that ICHEV's prediction can be compared with the results in Peterson et al. (2010)'s work (See Results section and Appendix B in detail).

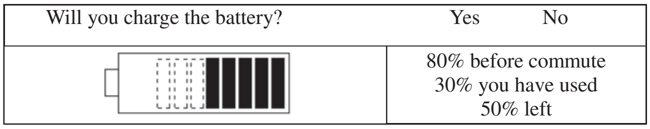

Fig. 3. A sample question of the EV battery charging survey.

Participants' personalities, decision making references, and charging strategies were derived from their self-report measures. It is assumed that $C_p = 795$ J kg^{-1} K^{-1}, Δheat = 0 and $N = 288$, and the ambient temperature is at a constant level: $T_0 = 10$ °C. The participant's battery charging frequency was then calculated using Equation (2). The driver characteristics, driving schedule, and predicted battery lifetime are shown in Table 1.

As shown in Table 1, the averaged predicted battery lifetime was 110.1 (SD = 26.6) months. GM expects that the lifetime of its EV battery should be no less than 96 months [25]. As a result, we compared the predicted battery lifetime with the expected lifetime using the One-Sample *T* Test (H_0:$\mu = 96$, H_1:$\mu > 96$). The result showed that we rejected the null hypothesis ($t(11) = 1.83$, $p = .047$) and concluded that the predicted battery lifetime was more than 96 months in this experiment. This was consistent with GM's published EV battery lifetime expectation and warranty [25], which meant that the EV battery could sustain longer than 96 months for the average driver.

In addition, before predicting the battery lifetime for each participant, we compared the capacity degradation between ICHEV's predictions and the simulated results from [9] based on the same driving variables in their study, and found no significant differences (See Appendix B). This also verified by the predicted lifetime from ICHEV.

4.5.2. Effects of driver characteristics and battery configuration on EV battery lifetime

In the second step, we performed regression analysis using SPSS [26]. Eleven variables entered as regressors: driver characteristics (personality, decision making reference, and charging strategy), driving schedule (driving distance on highway on the weekday, driving distance on highway on the weekend, driving distance on urban road on the weekday, and driving distance on urban road on the weekend), and battery configuration (heat capacity, heat reduction, the number of the cell, and initial temperature). To predict the battery lifetime, each battery configuration was assumed to have two levels: heat capacity ($C_p = 707$ or 1019 J kg^{-1} K^{-1}), heat reduction (Δheat = 0 or 34 W m^{-2} K), the number of the cell ($N = 200$ or 228), and initial temperature ($T_0 = 10$ or 30 °C). As a result, there were $2 \times 2 \times 2 \times 2 = 16$ combinations in which we changed the battery configuration to predict the battery lifetime.

The regression model accounted for 70% of the variability in the data set (adjusted R-square = 0.7). The ANOVA results showed that the overall regression was significant ($F(1,191) = 41.576$, $p < .0001$). The regression results indicated a significant decreasing effect of personality on battery lifetime ($t = -4.796$, $p < .0001$). Those drivers who were characterized as non-impulsive could use the battery for a longer period of time than impulsive or normal drivers. Charging strategy had a significant, negative effect on battery lifetime ($t = -3.986$, $p < .0001$). The battery lifetime was expected to increase 2.85 months when the charging strategy decreased by 1%. The initial temperature had a significant decreasing effect on battery lifetime ($t = -3.471$, $p = .01$). The battery lifetime was expected to decrease 1.38 months if the initial temperature increased 1 °C. All driving distance variables had significant, negative effects on battery lifetime: driving distance on the highway on the weekday ($t = -12.450$, $p < .0001$), driving distance on an urban road on the weekday ($t = -2.421$, $p = .016$), driving distance on the highway on the weekend ($t = -4.798$, $p < .0001$), and driving distance on an urban road on the weekend ($t = -6.938$, $p < .0001$).

Based on regression results, a linear equation was built to express the relationship between battery lifetime and all significant regressors (See Equation (6)). These factors included: personality, charging strategy, initial temperature T_0, driving distance on highway road on the weekday (D_{hd}), driving distance on urban road on the weekday (D_{ud}), driving distance on highway road on the weekend (D_{he}), and driving distance on urban road on the weekend (D_{ue}).

$$\begin{aligned} \text{Lifetime} = {} & 393.768 - 35.1552\text{Personality} - 2.85\text{Charging} \\ & - 1.382T_0 - 9.716D_{hd} - 2.592D_{ud} - 4.361D_{he} \\ & - 11.533D_{ue} \end{aligned} \tag{6}$$

4.5.3. Optimal battery configuration, driving patterns, and charging strategy

The optimal battery configuration was generated for all participants: the optimal heat capacity was 1020 J kg^{-1} K^{-1} (range = 700–1020 [27]), the optimal heat reduction was 380 W m^{-2} K (range = 0–380 [27]), and the optimal number of cells in the battery pack was 320 (range = 80–320 [28,36–38]) given $T_0 = 10$ °C. These results indicated that the maximal battery lifetime could be achieved by means of maximizing the heat capacity, heat reduction, and the number of cells in the pack. It is expected that battery manufacturers can mass produce battery packs following these optimal configurations and do not need to customize each pack for different drivers.

Table 1
Participants' characteristics, driving schedule, and predicted battery lifetime.

Participants (drivers)	Personality	DMR (mph)	Charging strategy (%)	Driving schedule (mile)				Predicted battery lifetime (months)
				Weekday		Weekend		
				Highway	Urban	Highway	Urban	
1	Normal	0	40	0	12	0	12	91
2	Impulsive	10	60	0	12	0	6	110
3	Non-impulsive	5	40	0	8	0	8	158
4	Normal	0	20	0	5	20	10	98
5	Non-impulsive	5	50	5	5	5	5	120
6	Normal	0	30	0	10	0	10	133
7	Non-impulsive	0	40	0	25	0	8	75
8	Normal	0	20	24	6	0	0	75
9	Normal	0	20	0	15	0	15	105
10	Impulsive	0	20	0	8	0	8	151
11	Impulsive	0	50	12	12	0	0	109
12	Normal	0	40	0	17	0	12	96

In the second step, the optimal driving patterns and charging strategy were predicted for the individual driver given the fixed battery configuration ($C_p = 1000.4$ J kg^{-1} K^{-1}, $N = 200$ Δheat $= 34$ W m^{-2} K and $T_0 = 10$ °C) and driving schedule (8.8 mile on the urban road and 7.2 mile on highway). The optimal acceleration (after the desired target speed was reached) was zero. The optimal changing frequency was roughly once every 2–5 days (See Table 2). For example, if a driver's optimal charging interval was 2.5 days, his/her best charging strategy was to charge the battery after two days, then recharge it after three days.

5. Software built based on the ICHEV

Software was developed to predict the battery lifetime and optimize the battery configuration, driving patterns, and charging strategy. User interfaces are shown in Fig. 4(a)–(c). In order to predict the battery lifetime, driver characteristics, including personality, decision making reference, and charging strategy, are needed. These measures could be collected from the driver's self-reports when he or she considers buying the EV. Driving schedule (daily driving distance and road types) could be estimated by the driver or automatically recorded by the advanced technologies installed in the car (e.g., GPS). For a specific type of EV battery, its configuration is fixed so that the lifetime can be predicted based on the driver characteristics and driving schedule (See Fig. 4(a)).

Another important function of the software was to optimize the battery configuration to prolong the battery life cycle. This could help EV manufacturers or engineers customize the battery configuration for each user. Specifically, when the driver considers buying the EV, he or she can provide the information about his/her personal characteristics (personality, DMR, and charging strategy) and estimate driving/living schedule. Given this information, the manufacturers can optimize the battery configuration (e.g., the thermal management module) to prolong the life cycle (See Fig. 4(b)).

Finally, the software was able to provide the driver the optimal driving patterns (speed and acceleration) and charging strategy to prolong the battery lifetime. As shown in Fig. 4(c), when the information about driving schedule and battery configuration were given, the optimal driving patterns and charging strategy could be predicted and presented via a visual/auditory or combined user interface. More importantly, when the information changed (e.g., real driving distance was much longer than the driver's expectation), the software could update the optimal driving and charging strategy in real time.

6. Discussion

In this work, an integrated computational human–electric vehicle (ICHEV) framework was developed to investigate the effects of the driver differences (personality, DMR, charging strategy, driving patterns, and driving schedule) and battery configuration on battery lifetime. This work was one of a few computational models that considers the effects of both human factors and engineering variables on the performance of the EV battery. ICHEV implemented in a desktop version of the driving simulator (STISM) provides a cost-effective and timesaving platform to test the effects of various driver behaviors on EV battery lifetime, compared to real EVs.

As a case study, a laboratory experiment using the driving simulator implemented ICHEV was conducted to predict the lifetime of Li-ion batteries in EVs. Driving patterns (e.g., driving speed and acceleration) were recorded from the driving simulator. Drivers' characteristics and driving schedule were collected and derived from the self-reported measures. According to the ICHEV, the predicted battery lifetime was no less than 96 months, which was consistent with the expectations and warranty of the EV battery manufactures (e.g., GM). Moreover, ICHEV's prediction is consistent with the results of other EV battery studies (e.g.Ref. [9]).

Additionally, the current experimental results show that the driver differences in personality, charging strategy, and driving schedule significantly affected the battery lifetime. The lifetime of batteries tended to be longer for those drivers who were characterized as non-impulsive, charged the battery less frequently and/or had a shorter driving distance for a daily commute.

Sequential quadratic programming (SQP) was used to optimize the battery configuration for the purpose of maximal battery lifetime. The results suggested that the maximal battery lifetime could be achieved by means of maximizing the heat capacity, heat reduction, and the number of cells in a battery pack. Nowadays, the typical heat capacity for a Li-ion battery is 795 J kg^{-1} K^{-1}, which is highly dependent on the chemical and physical material made of the battery [27]. Heat reduction relies on the type of thermal management module. For example, the heat transfer coefficient of oil is 1.5–3 times higher than air and the heat transfer rate of water for indirect cooling is about 15 times greater than air [27]. Accordingly, developing a convenient thermal management module with high-performance was expected to significantly prolong the battery lifetime. The third way to prolong the battery lifetime was to maximize the number of cells in the battery pack. However, this would increase the volume and cost the battery pack inevitably. Battery cells with smaller size and lower cost are more likely to achieve longer battery lifetime.

SQP was also performed to optimize the individual driver's driving patterns and charging strategy for the same purpose of maximal battery lifetime. The optimal acceleration was predicted to be 0 after a driver reached his/her desired target speed. This indicated that a driver should try his/her best to maintain a constant speed after reaching the desired speed and avoid stepping on the pedal too strongly (e.g., panic braking). Avoiding frequent and unnecessary battery charging is another way to prolong the battery lifetime. For example, do not charge the battery if the residual energy is enough for another daily commute. Since there are few charging links built currently, people can only charge the vehicle after the one day driving. GM has reported that a 240-V charging link will replenish the battery in about 4 h (where it takes 10 h using 120-V household current) [28]. With the development of the quick charging station, people may charge the battery at their work places or nearby. This will make the charging process more convenient and the charging frequency easy to reach the optimal value.

The users of ICHEV and its driving simulator can easily modify different driver characteristics, different road and traffic situations via setting the simulator, and different configurations of EV battery. According to the ICHEV, software was developed to predict the

Table 2
Optimal charging strategy.

Participants (drivers)	Optimal charging frequency (1/day)
1	0.3 (About once every 3 days)
2	0.4 (About once every 2 days)
3	0.3 (About once every 3 days)
4	0.4 (About once every 2 days)
5	0.3 (About once every 3 days)
6	0.2 (About once every 5 days
7	0.4 (Once every 2 days)
8	0.3(About once every 3 days)
9	0.2 (About once every 5 days)
10	0.2 (Once every 5 days)
11	0.5 (About once every 2 days
12	0.3 (Once every 3 days)

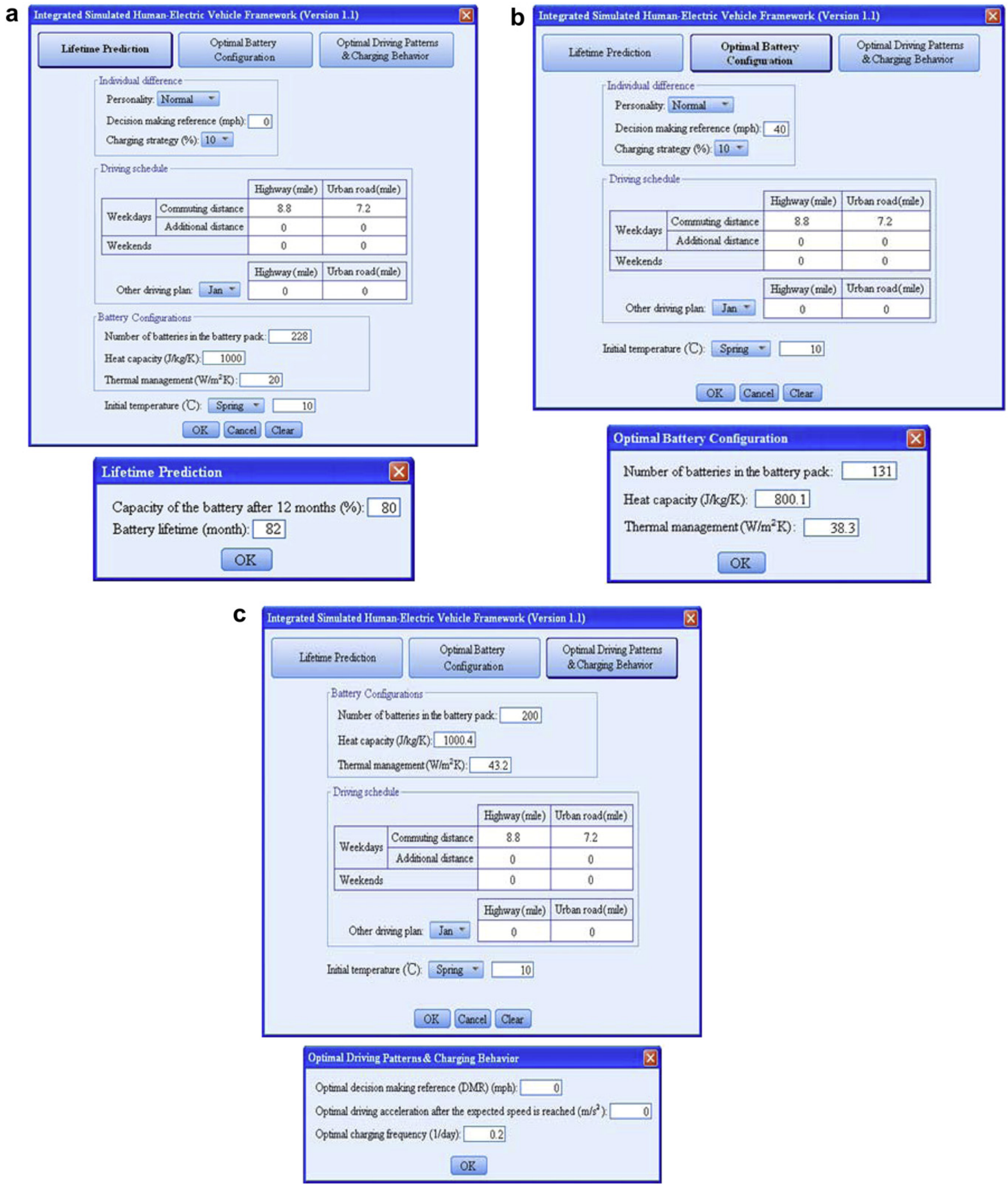

Fig. 4. (a). Prediction of the battery lifetime; (b). Optimal battery configuration; (c). Optimal driving patterns and charging strategy.

battery lifetime and optimize the battery configuration, driving patterns, and charging strategy. This software can be embedded in the computer system of the real car and has practical applications. For example, when a driver considers buying an EV, he or she can provide the information about his/her personal characteristics (such as personality and decision making reference) and estimate the daily driving schedule as possible. Given this information, the software can help the manufacturers or engineers customize the battery configuration for the maximal battery life cycle. Additionally, the software can provide the driver with the optimal driving and charging strategy via an in-vehicle human–machine interface (HMI). Also, if the real driving schedule (measured by the global position system or other technologies installed in the vehicle) is largely different from the driver's estimation (e.g., real driving distance is much longer than expectation), the software can provide the optimal driving and charging strategy in real time.

The current experimental settings using the driving simulator saved a large amount of time and money with ability to simulate various traffic and road situations. The current driving scenario in the experiment simulated a regular or daily driving situation in North America, but it can easily changed to highly congested driving situation in cities or other driving situations or different roads. Only 1 h was required per participant for this experiment. The cost of the driving simulator is only 2500 dollars, much less than a real EV. Compared to existing research, the framework in the current study took more comprehensive factors into account. In particular, this study considered the impact of human beings to the battery lifetime. Since the human is the real user of the vehicles, taking the human into account could establish a more complete human–electric vehicle system and predict the battery lifetime more accurately. Furthermore, for a specific driver whose personal characteristics are known, the optimal battery configuration could be predicted for the maximal battery lifetime. These predictions could be utilized by the battery manufactures to adjust the parameters of the battery for a certain type of driver. Similarly, for a certain type of EV battery (battery configuration is fixed), the driver could be informed of the optimal driving pattern and charging behavior to prolong the battery lifetime. Considering the high cost of the Li-ion battery, this study would provide high economic value for both battery manufactures and EV users.

In reality, it is possible to modify and improve driver behavior both in charging and driving the vehicle. For the optimal charging behavior, it is possible that we inform different drivers for their optimal charging frequency (See Table 2) via different messages or instructions in the vehicle (They can either be displayed on the dashboard of vehicles or played to drivers via speakers) when the vehicle is stopped. Empirical studies have shown that well-designed in-vehicle messages presented to drivers can modify driver behavior (E.g., Zhao & Wu, 2012) [39]. For the optimal driving behavior, this current work's optimal driving behavior is keeping the acceleration (after the desired target speed was reached) close to zero. We acknowledge that it is hard to modify driver behavior given the dynamic traffic flow and relatively stable human behavior pattern. However, in free-driving and straight road situations (no leading vehicle or it is very far from the current driver and there is no other vehicles nearby), empirical studies (e.g., Wu et al., 2011) showed that driver behavior can be changed to optimize the energy usage for vehicles via proper design of in-vehicle display and training [40].

There are some limitations in this study. Firstly, the experiment used a driving simulator to obtain the driver's driving profiles and charging strategy, which may be different from their real driving and charging behavior. Secondly, because of the high complexity of the Li-ion battery, some factors were not considered at the current stage due to their minor effects on battery lifetime (such as the loss of lithium). More studies of the EV battery in either real cars or simulated experimental settings are expected in the future to validate the framework and predictions of the ICHEV.

Acknowledgement

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Appendix A. Summary of the links, equations, parameter settings, and references

Table A
Summary of the links, equations, parameter settings, and references in the battery simulation module.

Link number	Link connection	Equation and description of each variable		Parameter setting and reference
(A)	Energy consumption ↓ Charging frequency	$f = \frac{E}{(1-q)\cdot Q}$ f is the charging frequency of the battery (1/day) E is the average daily energy consumption (J) q is the average percentage of the battery residual energy leading the driver charging the battery (%) Q is the battery capacity (J)	(2)	
(B)	Charging frequency and Operating temperature ↓ Battery lifetime	$\mathrm{LT} = \frac{167.583 - 1.264\cdot T - 100\cdot E/Q_0}{0.097\cdot f}$ T is the operating temperature of the EV battery (°C) Q_0 is the initial capacity of the battery when it is manufactured f is the charging frequency of the battery (1/day) LT is the time elapsed since the battery is manufactured (day)	(3)	$c_b = 167.583$ $c_T = -1.264$ $c_N = 0.097$ Ref. [30,31]
(C)	Voltage and Current ↓ Heat generation	$\dot{q}'_{\mathrm{gen}} = I'\left(U'_{\mathrm{ocv}} - U'_{\mathrm{op}}\right) - I'T\frac{\mathrm{d}U'_{\mathrm{ocv}}}{\mathrm{d}T}$ $\dot{q}'_{\mathrm{gen}}$ is the heat generation rate of one cell I' is the current of one cell (A) ($I > 0$ for discharge) U'_{ocv} is the open circuit voltage of one cell (V) U'_{op} is the operating voltage of one cell under load (V)	(7)	Ref. [32]

Table A (*continued*)

Link number	Link connection	Equation and description of each variable	Parameter setting and reference
(D)	SOC $\downarrow$ Voltage	$$U'_{ocv} = -1.031e^{-35\times SOC} + 3.658 + 0.2156 \times SOC - 0.1178 \times SOC^2 + 0.321 \times SOC^3 \quad (8)$$ SOC is state of charge	Ref. [33]
(E)	Energy consumption $\downarrow$ SOC	$$SOC = \frac{e}{Q} \quad (9)$$ e is the energy left in the battery (J)	
(F)	Voltage and Energy consumption $\downarrow$ Current	$$U_{op} = U_{ocv} - IZ_{eq} \quad (10)$$ $$P = U_{op} \cdot I = n \cdot U'_{op} \cdot I \quad (11)$$ $$I = \frac{n \cdot U'_{ocv} - \sqrt{\left(n \cdot U'_{ocv}\right)^2 - 4Z_{eq} \cdot P}}{2Z_{eq}} \quad (12)$$ U_{op} is the operating voltage of the battery pack under load (V) U_{ocv} is the open circuit voltage of the battery pack (V) I is the current of the battery pack (A) ($I > 0$ for discharge) Z_{eq} is the internal impedance of the battery pack (Ohm) P is the power consumption of the battery pack (W) n is the number of cells in a serial within the battery pack U'_{op} is the operating voltage of one cell under load (V)	
(G)	Heat generation $\downarrow$ Thermal management Thermal management, discharge rate, and heat capacity $\downarrow$ Operating temperature	$$T = T_0 + \Delta T = T_0 + c_a + c_t \cdot t' + c_R \cdot C_R + c_H \left(\frac{\sum \dot{q}\Delta t}{t' \cdot N} - \frac{\Delta heat}{N}\right) + c_c \cdot C_p \quad (13)$$ T_0 is the initial temperature of the battery during the operation process (°C) Δt is the time interval the driving profile is recorded by the related device (s) t' is continues operation time of the battery in one time (s) C_R is the discharge rate of the battery $\dot{q}$ is the heat generation rate of the battery pack (W) N is the number of cells in one battery pack Δheat is the difference heat transfer rate generated by other types of cooling module comparing to the air-cooling module (W m $^{-2}$ K) C_P is the heat capacity of the battery (J kg^{-1} K^{-1})	$c_a = 0.0339$ $c_t = 0.004$ $c_R = 0.001$ $c_H = 2.385$ $c_c = -0.004$ $C_R = P/1.25, P/2, P/3$ $C_P = 707$ or 1019 Ref. [27]
(H)	Speed and acceleration/ deceleration $\downarrow$ Energy consumption	$$p = \left(ma + \frac{1}{2}\rho v^2 C_d A + C_{rr} mg\right) 0.4v \quad (14)$$ $$p = \frac{\left(ma + \frac{1}{2}\rho v^2 C_d A + C_{rr} mg\right) v}{0.8} \quad (15)$$ p is power consumption for vehicle motion (W) m is the mass of the vehicle (kg) v is the velocity of the vehicle (m s^{-1}) a is the acceleration of the vehicle (m s^{-2}) ρ is roughly air weight at sea level (kg m^{-3}) C_d is the vehicle's coefficient of drag C_{rr} is the coefficient of rolling resistance for the tires A is frontal area of the vehicle (m^2)	Ref. [9,34] $m = 1588$ $A = 2.67$ $\rho = 1.23$ $C_d = 0.28$ $C_{rr} = 0.01$ Ref. [9,35]

(*continued on next page*)

Table A (*continued*)

Link number	Link connection	Equation and description of each variable	Parameter setting and reference
(I)	Current ↓ Discharge Rate	$C_R = \frac{I'}{I'_{rate}}$ (16) I'_{rate} is the rated current of one battery pack (I)	
(J)	Current and Voltage ↓ Overcharge/over-discharge protection ↓ Lifetime	There are no equations in Link J. The overcharge/discharge protection is used to prevent the current or voltage becoming too high. The high voltage or current is harmful to the battery and may destroy the battery in a short time.	Ref. [32]

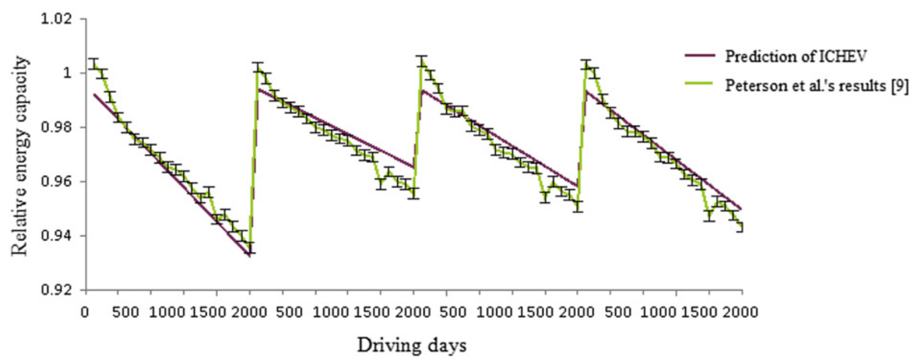

Fig. A. Comparisons of modeled capacity degradation in current study with simulated capacity degradation in Ref. [9].

Appendix B. Validation of the battery simulation and lifetime prediction module

Peterson et al. (2010) constructed a simple physics model to compute the energy needed to propel a typical electric vehicle. The driving profile was created by sampling the Urban Dynamometer Driving Schedule (UDDS) [29]. The testing was conducted with Arbin BT2000 series battery cyclers to simulate the charge–discharge cycles of the Li-ion battery in EV. Each cycle represented a single driving day. In this study, ICHEV's predictions of the capacity degradation were compared to Peterson's results using Paired Samples Test. It was shown that there was no significant difference between Peterson's simulated results and ICHEV's predictions ($t = -1.44$, $p > .05$).

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