Battery-Aware Energy-Optimal Electric Vehicle Driving Management

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***Abstract*—Recently, Electric Vehicles (EVs) have been considered as new paradigm of transportation in order to solve environmental concerns, e.g. air pollution. However, EVs pose new challenges regarding their Battery LifeTime (BLT), energy consumption, and energy costs related to battery charging. The EV power consumption may be estimated by having the route information and the EV specifications. Also, by having the battery characteristics, the battery capacity consumption and the BLT may be estimated for each route. In this paper, we propose a driving management which uses the above-mentioned information in order to optimize the driving route by being aware of the EV energy consumption, energy cost, and BLT. Our proposed driving management extends the BLT by 16.8% and reduces the energy consumption by 11.9% and energy cost by 12.6% on average, by selecting the optimized route instead of the fastest route.**

I. Introduction and Related Works

In 2012, transportation accounted for about 28% of total U.S. greenhouse gas emissions, making it the second largest contributor of U.S. [1]. To tackle this alarming situation and other environmental concerns such as, global warming, air pollution, and noise pollution, Electric Vehicles (EVs) have been seen as the new paradigm of transportation [2]. However, deploying EVs poses new challenges. EVs rely on electricity for their electrical propulsion motor mainly provided by the battery. Therefore, the driving range of EVs is limited to the battery capacity, which causes *"range anxiety"* for drivers [3]. Also, because of the higher cost of replacing the battery, e.g. 12,000$ for Tesla Model S 85KWh [4] and 5,500$ for Nissan Leaf S [5], extending the Battery LifeTime (BLT) and/or operational time has been seen as one of the most important research challenges in adopting EVs economically. It has been shown that an intelligent and advanced Battery Management System (BMS), built upon the capability of monitoring and managing the discharge pattern of the battery may decrease the EV energy consumption, the required battery capacity, and extend the BLT by utilizing the battery more efficiently and intelligently [6], [7].

In [8], it has been shown that BMS may be correlated to route selection or driving management. Hence, the authors have proposed a route selection algorithm which considers traffic and energy consumption, in order to find the optimum route. Their solution is limited to finding the optimum route just for avoiding the *"range anxiety"* that an EV may cause, at a particular time (short-term decision making) and does not consider the BLT. Moreover, [9] has proposed an algorithm to find the most efficient route based on the data gathered from the vehicle efficiency. Existing driving managements do not consider BLT, where it is a property that is affected by consecutive EV usages pattern by the user and its value cannot be estimated unless in the long run. Therefore, users may need to take informed decision of their route selection everyday based on the battery characteristics.

A. Motivational Case Study on Vehicle Fuel Economy

To understand the vehicle's fuel economy under various speeds, we have performed an experiment using the available data found in the existing literature [4], [10]. We have compared the relationship between the fuel economy and speed in an EV, with an Internal Combustion Engine (ICE) vehicle. Our experiment shows that, EVs and ICE vehicles have very different characteristics and complexities. As shown in Fig. 1, the efficiency of an ICE vehicle is almost at its maximum when driving around 40-60 miles per hour (mph). However, for an EV the efficiency drops significantly as the speed increases to more than 25mph. Moreover, the available battery capacity decreases in higher discharge-rates (rate-capacity effect) [11] (see Section II-C for more details). Therefore, if we consider this effect, the fuel economy of the EVs might change significantly.

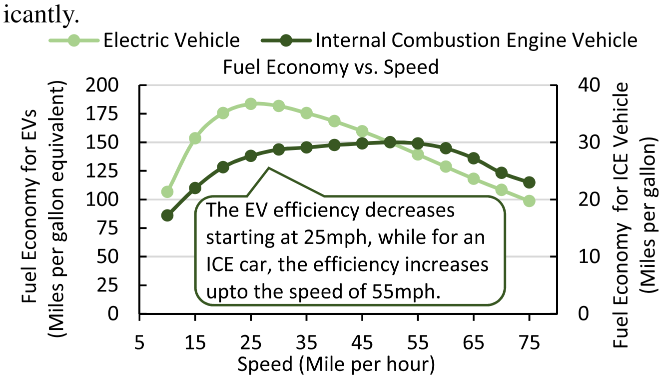

Fig. 1. Fuel Economy Comparison between an EV, e.g. Tesla Model S and an ICE Vehicle [4] [10].

Summary and conclusion from observations: the observation shows that the characteristics of the EVs and ICE vehicles are different. Moreover, the fuel economy of the EV is also highly dependable on the battery characteristics. Therefore, it has been verified that the existing solutions [9] from ICE domain may not be adopted for efficient driving management or route selection for the EVs.

On the other hand, according to the EV roadmap [12], the number of EVs expected to penetrate into the power grid is very high. This is a very positive road map from the greenhouse gas emissions point of view, but it will create new challenges for the existing power grid. The electricity load (power) demanded by EV chargers is mainly related to their charging rates, e.g. Level I, Level II, and Level III chargers consume about 1.4KW, 3.3-6.6KW, and 50-70KW, respectively [13]. Therefore, the increase in EV penetration level may impact the electricity consumption pattern by increasing the daily peaks [14]. The increase in the peak load demand may also result in thermal overloading, voltage drop, and transformer efficiency drop [15]. To address these concerns, different battery charging algorithms for managing and shifting the load demand have been proposed. In [12], authors have analyzed the impact of EVs on the load shape and compared it with the case in which the Time-Of-Use (TOU) rates have been applied for load shifting. Since the route where the EV is driving in, affects its energy consumption, it will also influence the energy consumed from the power grid and the energy cost to recharge the battery. Therefore, by driving management or route selection, the driver may be able to decrease the power grid energy consumption and energy cost, by having adequate information from the power grid.

B. Problem and Research Challenges

The problem of maximizing the electric vehicle battery lifetime while minimizing the energy consumption and cost by driving management poses the following key challenges:

- Existing driving managements do not consider the battery characteristics for managing the driving:
  - Battery rate-capacity effect has not been considered for evaluating the energy consumption and range prediction.
  - Battery operational time has not been accounted into decisions for driving management, besides energy consumption and cost minimization.
- They also have not accounted the energy consumption and energy cost from the power grid into driving management.

C. Our Novel Contributions and Concept Review

To address the above-mentioned challenges, a novel driving management for maximizing the battery lifetime and minimizing the energy consumption and cost is proposed that employs:

1) **Modeling and Estimation of EVs (Section II)** which models and estimates the EV power train consumption using multiple variables, e.g. speed, acceleration, and etc.
2) **Modeling and Estimation of Battery (Section II-C)** which models the battery characteristics, in order to estimate the influence of EV power consumption on BLT.
3) **Modeling and Estimation of Power Grid (Section II-D)** which models the power grid and battery charging, in order to estimate the energy consumption and energy cost related to the battery charging.
4) **Energy-Optimal Battery-Aware Driving Management (Section III)**, based on the proposed modeling and estimations, minimizes the battery lifetime in the EVs by managing the driving, e.g. route selection, while minimizing the energy consumption and energy cost from the power grid.
5) **Experimenting and Analyzing the Driving Management Influence (Section IV)** on the BLT, energy consumption, and energy cost for multiple state-of-the-art benchmark EVs, e.g. Tesla, Nissan, and Fiat.

Fig. 2 describes our novel driving management methodology for maximizing the battery lifetime and minimizing the energy consumption and energy cost.

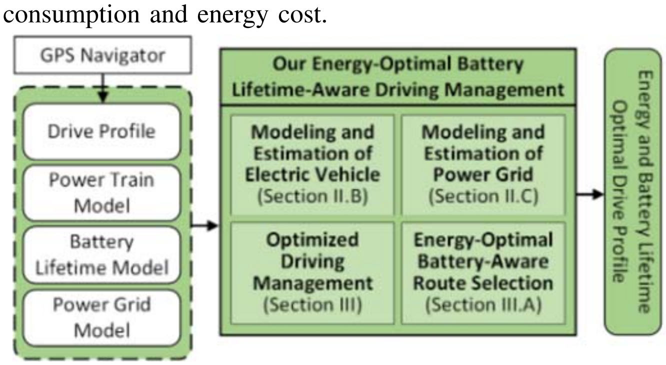

Fig. 2. Energy-Optimal Driving Management Methodology for Maximizing the Battery Lifetime.

II. System Modeling and Estimation

The information about the driving route (Section II-A) enables us to evaluate the EV power train consumption at each instance of time by having the power train model (Section II-B). Since the EV power is mainly provided by the battery, the current drawn from the battery is evaluated based on the previously measured power consumption. By having the battery model (Section II-C), the instantaneous battery capacity and the BLT will be evaluated. Moreover, by knowing the power grid model and the battery charging algorithm (Section II-D), the energy consumed from the grid and the cost of recharging the battery are evaluated.

A. Route Condition Model

Nowadays, drivers typically utilize GPS-based navigation systems to help them find the route to their destination. Hence, the route information such as the route segments, route length, and route duration, is known before driving. Other information about the route such as route slope may be gathered from the existing databases [16]. Gathering this information may help us to precisely model the route. A *drive profile* is defined, to encapsulate the route information into a multi-variable array. The drive profile consists of *the route slope, the average speed of the EV, and the route length*. The information used for generating the drive profile can also be generated from standard drive cycles which are typically used for testing, simulation, and verification of vehicles, e.g. NEDC [17]. The structure of the drive profile includes: 1) the steps to reach the destination (s); 2) the length of each step (ι_s); 3) the average speed of the vehicle in each step (υ_s); and 4) the slope of the route in each step (α_s). Therefore the drive profile is a vector of n tuples ($\iota_s\ \upsilon_s\ \alpha_s$), in which n is the number of steps in the route.

B. Power Train Model

By providing the drive profile to the EV model, the power requirements for the EV are measured. Fig. 3 shows an EV architecture to help understanding our EV model.

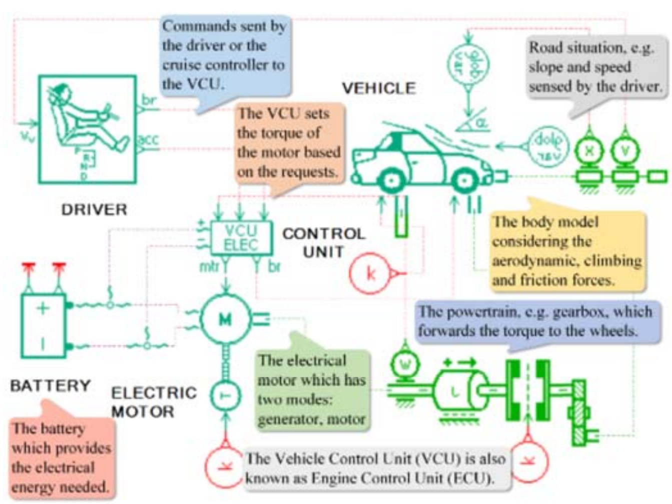

Fig. 3. System-level EV model Developed in the AMESim Tool [18].

In our EV model, all the forces such as: F_{cl}, F_{aero}, and F_{roll} which may affect the vehicle motion in terms of speed and acceleration, are summed as resistive force (F_{res}) [18]. F_{cl} is the force caused by the gravity in different route slopes. The α variable in Eq. 1 is the percentage of the route slope, e.g. 100% value for α represents the route slope of $45°$. m is the vehicle mass and g is the gravitational constant. F_{aero} is the aerodynamic drag force caused by the air striking the vehicle body. This force depends on the vehicle speed (v), wind speed (V_{wind}), air density (ρ_{air}), penetration coefficient (C_x), and vehicle active area (S) (Eq. 2). Since, the vehicle speed affects the force quadratically, it may limit the vehicle top speed. F_{roll} is the rolling friction force resisting the motion of the wheels and tires. The equation for F_{roll} has one constant (f) and two proportional friction coefficients ($K, wind$) (Eq. 3) which depend on the vehicle specifications.

$$F_{cl} = m \times g \times \sin(\arctan(0.01 \times \alpha)) \quad (N) \tag{1}$$

$$F_{aero} = 1/2 \times \rho_{air} \times C_x \times S \times (v + V_{wind})^2 \quad (N) \tag{2}$$

$$F_{roll} = m \times g \times (f + K \times v + wind \times v^2) \quad (N) \tag{3}$$

The forces generated by the components inside a vehicle, e.g. the electric motor (F_{dr}) and the brake (F_{brake}) are summed as the total force (F_{tot}). The resulting acceleration of the vehicle depends on the subtraction of F_{res} from F_{tot} and the vehicle mass (see Eq. 4).

$$a = \frac{F_{tot} - F_{res}}{m} \quad (m/s^2) \tag{4}$$

When F_{res} is positive and the speed needs to be maintained, the vehicle should provide enough forward force to prevent deceleration. In this case, the force is generated only by the electric motor (F_{dr}). On the other hand, when F_{res} is negative and the speed needs to be maintained, the vehicle needs to provide backward force to prevent acceleration. In this case, the force may be generated by the electric motor and the brakes. The force generated by the electric motor is due to the generation mode ($F_{dr} < 0$), is limited to F_{min}, and may not provide enough backward force to neutralize the resistive force (Eq. 5). Therefore, the rest of the backward force is generated by the braking pads (Eq. 6).

$$F_{dr} = max(F_{min}, F_{tot}) \quad (N) \tag{5}$$

$$F_{brake} = F_{dr} - F_{tot} \quad (N) \tag{6}$$

The mechanical power that drives the vehicle is the multiplication of F_{dr} and v. Moreover, the electric motor has an energy conversion efficiency (η_{motor}) less than 100% and it varies by the torque and the rotational speed [19] (Eq. 7).

$$I = \frac{P_{elec}}{V_{dc}} \quad (A) \quad P_{elec} = \frac{F_{dr} \times v}{\eta_{motor}} \quad (W) \tag{7}$$

In this paper, the specifications for three EVs (Tesla Model S 60KWh, Nissan Leaf S, and Fiat 500e) have been used to validate the power train model [4] [5] [20].

C. EV Battery Model

The battery is mainly providing the power for the EV, therefore, an accurate battery model may help us to estimate the precise battery consumption and its influence on the BLT. Moreover, the battery pack structure is important for modeling the battery. The specification for the battery pack used in our experimental three EVs may be found in [4] [5] [20]. The nominal capacity (C_n) of the battery pack depends on the structure and each battery cell capacity [21]. The battery cell nominal capacity is measured at the discharge rate of ($I_n = 0.2C$) [22]. The C rate is the discharge rate in which the battery depletes in one hour.

Lithium-ion batteries are mainly used in EVs, and as we have stated before, the usable capacity of these batteries may vary based on the discharge rate (capacity-rate effect). This effect is empirically modeled as Peukert's Law [23]. For instance, according to [22], by increasing the discharge rate from $0.2C$ to $2C$ the discharged capacity of the battery decreases from $2857mAh$ to $2500mAh$ at the cut-off voltage of about $3.2v$. The relationship between the usable capacity and the discharge rate is expressed in Eq. 8, in which pc is the *Peukert Constant* which is measured for each battery type. The equation shows that by increasing the discharge rate, the efficiency of converting chemical energy to electrical energy decreases and more chemical reactions are needed to provide the same electrical energy. Therefore, the effective current increases more by increasing the discharge rate (Eq. 9) which results in lower usable capacity.

$$C = C_n (I_n/I)^{pc-1} \quad (Ah) \tag{8}$$

$$I_{eff} = I (I/I_n)^{pc-1} \quad (A) \tag{9}$$

The State of Charge (SoC) of a battery shows the battery state at that moment and how much capacity still has remained, out of C_n. As you see in Eq. 10, the effective current is considered in the estimation of the SoC. And, as the discharge rate increases, the changing rate of SoC increases hyperbolically. SoC^0 is the initial SoC at time zero.

$$SoC^t = SoC^0 - 100 \times \int_0^t (I_{eff}/C_n)\, dt \tag{10}$$

Using the power train and the battery models of three EVs (Nissan, Fiat, and Tesla), we have evaluated the driving range of the EVs for different speeds. The results (see Fig. 4) show that the usable capacity of the battery changes for different speeds. This verifies that considering the battery model in estimating the EV driving range may be essential for driving management.

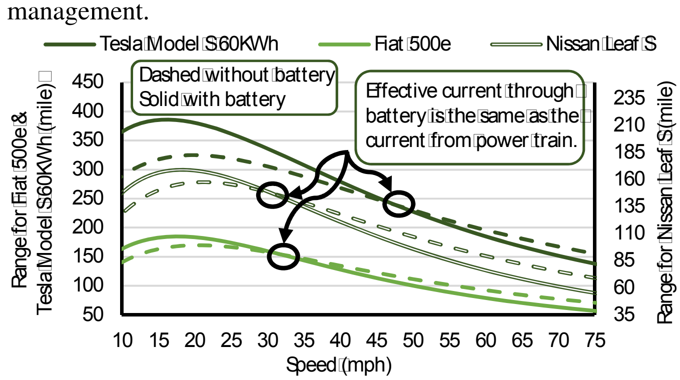

Fig. 4. Estimated EV Range w/ or w/o Considering the Battery Model.

The battery Depth of Discharge (DoD) shows how much capacity has been used out of C_n in one cycle of the battery use. C_n degrades as the battery ages in each cycle. The capacity degradation rate depends on the DoD [6]. After about 20% of capacity degradation, the battery will become useless. The BLT is the number of cycles the battery can be used until the cut-off edge. For instance, as shown in [24], by increasing the DoD from 20% to 50%, BLT decreases from 2100 to 1000. Based on this observation and the data set presented in [24], the relationship between the BLT and the DoD is approximately modeled in Eq. 11. The constants α and β are measured for different types of batteries.

$$BLT = \alpha \times (1/DoD)^{\beta} \quad (cycles) \tag{11}$$

In this battery model, it is assumed that the battery cells are utilized evenly while powering the EV. The aging effect, capacity degradation, and the decrease in usable capacity are distributed evenly among all the battery cells. This assumption is not an overestimation as per paper [25], where the proposed configuration and scheduler may manage the even distribution of the power on the battery cells [21].

D. Power Grid Model

The EV batteries are typically recharged by connecting them to the power grid. Hence, knowing the power grid specifications and characteristics may help us to analyze and optimize the influence of EV driving management on the power grid side, e.g. energy consumption and energy cost.

To charge an EV, drivers may use the ordinary 110v outlet existing in the U.S. houses (Level I) or use the 220v outlet for faster charging (Level II). However, they may utilize other power electronics like super chargers to make the charging process faster. Each charger has its own specifications in case of charging rate, power, and cost. The charging rate may be variable and can be adjusted by the battery charging controller.

Utilities providing electricity may have different pricing policies [12]. For instance, in the first case, the electricity rate is constant throughout the day (*Flat Rates*). However, in the second case, the electricity rate changes based on the Time-Of-Use (TOU), in order for the Utilities to reduce the electricity demand peak. As opposed to *Flat Rates* case, in *TOU Rates* case, the users have incentive to change the battery charging time such they minimize the energy cost of recharging. As shown in Table. I, in the *TOU Rates* case, on-peak hours ends at 10pm. Therefore, most of the charging time may be scheduled from 10pm until the departure time, to reduce the charging cost. However, in the *Flat Rates* case, the charging time may be scheduled as soon as the driver arrives home.

TABLE I. SPECIFICATIONS OF THE POWER GRID.

Name	Property		Value
Electricity Rate	TOU Rates ($/KWh)	On-peak (11am-10pm)	0.15085
		Off-peak (10pm-11am)	0.01514
	Flat Rates ($/KWh)		0.06507

A driver may decide to use the battery partially and charge the battery every day to the full state instead of discharging completely to zero and charging back to the full state, for example, every week. In this case, the DoD decreases and the BLT increases. However, as stated in [24], *Ah throughput* is going to be the same which results in the same capacity degradation. Therefore, the aforementioned charging patterns of the battery may have a negligible effect on the BLT. Charging and discharging the battery partially decreases the charging time and may provide the driver with the flexibility of deciding on the charging schedule. For instance, the driver may choose to follow the earlier pattern and charge the vehicle during the midnight when the electricity price is lower. However, in the later pattern, the charging period is the maximum and it may overlap with the time when the electricity price is higher.

In the chosen battery charging algorithm, as part of the power grid model, we use the partial charging pattern. Algorithm 1 illustrates a pseudo-code which schedules the battery charging such that it reduces the energy cost while meeting the departure time of the user. The algorithm receives user-specified departure time ($0 \leq t_d \leq 23$), the current time of the day ($0 \leq t_c \leq 23$), and the current battery status ($0 \leq SoC \leq 100$). The outputs of the algorithm are the estimated energy consumption (*energy*), energy cost (*cost*), and the adjusted current to charge the EV battery (I). The total battery capacity (Cap), the start time (t_{os}) and end time (t_{oe}) for the off-peak hours, the electricity rates ($\$_{on}, \$_{on}$), and the maximum charge rate which the charger is able to provide (max_I), are defined (lines 1-6). In line 7, the remaining battery capacity which needs to be charged is evaluated using SoC. In line 8, the length of the time interval when there is off-peak hours until the departure time, is evaluated. In line 9, the optimum charge rate during the off-peak hours is evaluated. In line 10, the amount of the battery which will be charged during off-peak hours is evaluated. In lines 11-12, the remaining battery capacity which needs to be charged during on-peak hours and the length of the time interval when there is on-peak hours are evaluated. In line 13, the optimum charge rate during the on-peak hours is evaluated. The charge rates are limited to the maximum charge rate, in lines 9 and 13. In line 14, the amount of the battery which will be charged during on-peak hours is evaluated. The total energy consumption and energy cost are estimated in lines 15-16. Eventually, the charge rate is assigned based on the current time (lines 17-20).

Algorithm 1: EV Battery Charging Algorithm

```
   Input: Departure Time td
   Input: Current Time tc
   Input: Battery Status SoC
   Output: Estimated Energy Consumption energy
   Output: Estimated Energy Cost cost
   Output: Charge Rate I
   // define the battery total capacity
1  Cap = 60K Wh
   // define start and end time for off-peak hours
2  tos = 22
3  toe = 11
   // define electricity rates from Utility
4  $on = 0:15085
5  $off = 0:01514
   // define the maximum charge rate possible
6  maxI = 4K W

   // evaluate capacity remaining to charge
7  Caprem = (100 □ SoC)=100 □ Cap
   // time interval when there is off-peak hours
8  Timeoff = (min(toe; td) □ max(tos; tc))%24
   // the charge rate during off-peak hours
9  Ioff = min(maxI ; Caprem=Timeoff)
   // the charged capacity during off-peak hours
10 Chargedoff = Ioff □ Timeoff
   /* evaluate capacity remaining after charging
      during off-peak hours                          */
11 Caprem = Caprem □ Chargedoff
   /* the time interval remaining to charge
      subtracting the off-peak hours                 */
12 Timerem = (td □ tc □ Timeoff)%24
   // the charge rate during on-peak hours
13 Ion = min(maxI ; Caprem=Timerem)
   // the charged capacity during on-peak hours
14 Chargedon = Ion □ Timeon
   // the estimated total energy consumption
15 energy = Chargedon + Chargedoff
   // the estimated energy cost
16 cost = Chargedon □ $off + Chargedoff □ $on

   /* deciding the current charge rate based on
      time                                           */
17 if tc 2 off-peak then
18   I = Ioff
19 else
20   I = Ion
21 return energy; cost; I
```

III. Optimal Driving Management

By having the start and end points of the driving, multiple alternative routes may be generated and their detailed information is stored as drive profiles (see Section II-A). The power train model estimates the power consumption of the EV based on the drive profile (see Section II-B). The power consumed in the EV is provided by the battery. Therefore, the battery consumption and the BLT are estimated using the detailed battery model (see Section II-C). The EV battery will be recharged by connecting to the power grid (see Section II-D). An algorithm may be implemented to recharge the EV battery intelligently in order to reduce the energy cost according to the Utility's specifications (see Algorithm 1). Therefore, each drive profile will result in a specific route duration, energy consumption, energy cost, and BLT. By having all the above-mentioned information, the driving management optimizes the route in order to extend the BLT and reduce the energy consumption and energy cost while maintaining the timing requirements for the route.

A. Optimized Route Selection

All the models, equations, and algorithms described in previous sections enable us to find the energy-optimal and battery-aware route. The driving management which tries to find the optimized route may be formulated as a mixed integer non-linear programming optimization problem:

$$\begin{array}{ll} min. & \alpha\ cost + \beta\ energy - \gamma\ BLT \\ subject\ to: & Alternatives = map\ (start,\ end) \\ & \forall\ drive\text{-}profile\ \in Alternatives \\ & T = drive\text{-}profile\ [\text{"}time\text{"}] \\ & P = power\text{-}train\text{-}model\ (drive\text{-}profile) \\ & (BLT,\ SoC) = battery\text{-}model\ (P) \\ & (cost,\ energy) = power\text{-}grid\text{-}model\ (SoC) \\ & 0\ \leq\ T\ \leq\ \overline{T} \end{array} \quad (12)$$

The objective of this optimization problem (Eq. 12) is to minimize the energy consumption (*energy*) and the energy cost (*cost*) and maximize the battery operational time (*BLT*). Each variable has a weight of optimization ($\alpha,\ \beta,\ and\ \gamma$). The selection of the drive profile (*drive-profile*) must be done among the alternatives found by giving the *start* and *end* points of the route. The equations, models, and algorithms are formulated as non-linear constraints in the optimization. The route duration (T) is extracted from the drive profile (*drive-profile*). An array representing the EV power consumption (P) is evaluated by the power train model (see Section II-B), by having the drive profile (*drive-profile*). The battery model (see Section II-C) will evaluate the battery operational time (*BLT*) and the final *SoC*, using P. The energy consumption and energy cost are estimated by using the power grid model (see Section II-D), knowing the battery status (*SoC*). Moreover, the route duration (T) is limited to $\overline{T}$, such that the optimizer does not sacrifice the time (for energy consumption, energy cost, or BLT) more than the driver's preferences.

IV. Experimental Results

A. Experimental Setup

The Google APIs [16] are used to provide the information needed for the drive profiles. For our experiment, multiple routes in which ordinary drivers who commute from their house at *"omitted for blind review"* to their office at *"omitted for blind review"* and return, in a daily manner, are used as drive profiles (see Fig. 5). Also, three different EVs (Tesla, Fiat, and Nissan) have been used as the study cases, in order to analyze the influence of the route selection for various EVs.

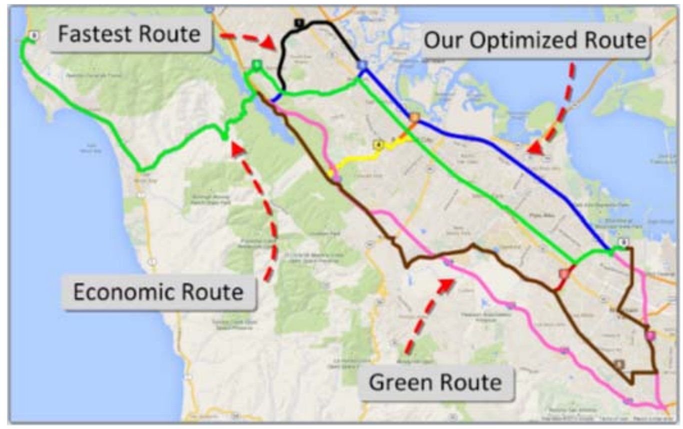

Fig. 5. Map Showing All the Alternative Routes. The Routes for Comparison are Also Labeled. (the figure is more visible in color printed version)

To implement the optimization problem, various multi-domain co-simulations have been performed using AMESim [18], an automotive design software, MATLAB/Simulink [26], and GridMat [27].

B. Comparison to the State-of-the-Arts

Different driving managements have been co-simulated for multiple drive profiles in three EVs. We compare our optimal driving management (see Section III) with three other state-of-the-art driving managements. All the driving managements have selected the following routes (see Fig. 5):

1) ***Fastest Route:*** the route with the least duration time is selected [16].
2) ***Economic Route:*** the route with the least amount of energy consumption is used [8].
3) ***Green Route:*** the route with the least fuel consumption for ICE vehicles is selected [9].
4) ***Our Optimized Route:*** the optimal route which extends the BLT and minimizes the energy consumption and energy cost (using the optimization problem in Section III).

Energy Consumption: the drive profiles selected by the above-mentioned driving managements have been co-simulated. The energy consumed from the power grid for recharging the EV batteries is shown in Fig. 6. The results show that by sacrificing about 3 minutes, our optimized route shows 11.9% energy consumption reduction on average, compared to the fastest route.

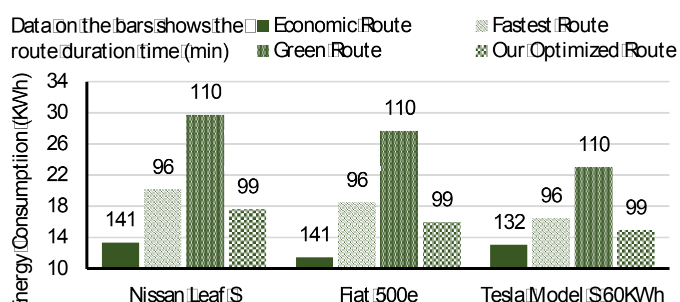

Fig. 6. Analysis of Energy Consumption for Recharging the EV Batteries in Different Driving Managements.

Battery Lifetime: the influence of the EV power consumption on the EV batteries has been analyzed. Based on the equations in Section II-C, the BLT has been estimated for the drive profiles selected by different driving managements (see Fig. 7). The results show that using our optimized route instead of the fastest route, will result in 16.8% BLT extension on average.

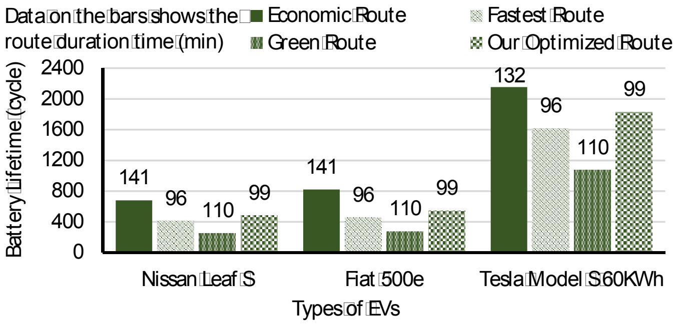

Fig. 7. Battery Lifetime Analysis in Different Driving Managements.

Energy Cost: the cost of charging the Nissan Leaf batteries after co-simulating the drive profiles selected by the driving managements, has been evaluated for two cases of *TOU Rates* and *Flat Rates* (see Fig. 8). The results show that the cost of recharging the batteries has reduced 12.6% on average, by using our optimized route instead of the fastest route.

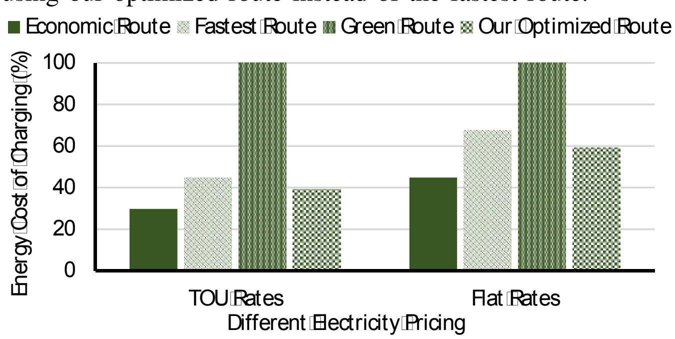

Fig. 8. Energy Cost Analysis for Two Electricity Pricing.

V. Conclusion

The deployment of EVs is growing rapidly, mainly because they provide zero-emission solution for transportation. However, EVs pose new research challenges in terms of their battery lifetime, energy consumption, and the energy cost of recharging the batteries. In this paper, we have proposed a novel driving management which utilizes the detailed EV model, battery model, and power grid model, in order to estimate EV power consumption, BLT, energy consumption, and energy cost. Based on the estimated values, the driving management selects an optimized route such that it extends the BLT and minimizes the energy consumption and energy cost for short-term and long-term uses. Our driving management has been applied to three EVs. The results have shown that using our optimized route instead of the fastest route, may increase the driving time by 3 minutes. However, the energy consumption and energy cost may reduce by 11.9% and 12.6%, respectively, and the BLT may extend by 16.8%.

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