# Survey of Low-Power Electric Vehicles: A Design Automation Perspective

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## I. Introduction

Electric vehicles have many fundamental advantages over internal combustion engine vehicles. Electric vehicle idea is not new. As early as in 1891, William Morrison of Des Moines, Iowa already built the first successful electric vehicle in the United States. However, internal combustion engines almost completely replaced electric powertrains in the production vehicles for the past 100 years.

Thanks to recent evolution of Lithium-ion batteries and strong demand for zero-emission vehicles, electric vehicles have successfully repositioned demonstrating commercial success. Nevertheless, electric vehicles still have challenges in terms of the battery weight, fully-charged driving range, costs, etc. In this survey, we provide range of information toward "low-power" electric vehicles that is able to inspire how design automation can overcome such primary electric vehicles' disadvantages more systematically and more efficiently.

We first introduce propulsion power modeling, estimation, runtime optimization, and design-time optimization in Section II as majority of battery energy in the electric vehicles is used for propulsion. Section III introduces driving profile modeling, estimation and runtime optimization on the top of Section II. Driving profile also largely impacts on non-propulsion power consumption. Indeed, modern electric vehicles also consume significant amount of battery energy for non-propulsion power such as heating, ventilation, and air conditioning. Section IV summarizes non-propulsion power modeling, estimation and runtime optimization. As battery systems are the key component for electric vehicles, we introduce modeling, simulation, estimation, and optimization of electric vehicle battery systems in Section V. Energy harvesting is a proactive way to manage electric vehicle energy. Section VI also summarizes vehicle energy harvesting methods including solar energy, wind energy, regenerative shock absorbers, and regenerative brakes. Section VII summarizes how electric vehicle charging impacts on the power grids. This section also points out unsolved issues and future research direction.

## II. Propulsion Power Modeling, Estimation, Runtime Optimization, and Design-Time Optimization

Electric vehicles of course consume majority of electrical energy for propulsion. Electric vehicle propulsion energy generally increases proportionally to their weight but also largely variable by the driving conditions such as road slope. Unfortunately, electric vehicles are not lighter than the similar scale of internal combustion engine vehicles due to the battery weight while production electric vehicles deploy light materials such as aluminum to a large portion of chassis and bodies to compensate the battery weight. For instance, Chevrolet Bolt (164" long) weighs 3563 lbs, but a Honda Civic (177" long) does only 2752 lbs.

Electric powertrain efficiency is already close to the their theoretical limits. Electric vehicles also have advantages in well-to-wheel efficiency from idling, downhill driving and braking using regenerative braking. Nevertheless, the well-to-wheel efficiency of electric vehicles is not much higher than that of internal combustion engine vehicles. Regenerative braking is fundamental advantage of electric vehicles that reclaim kinetic energy back to electrical energy, which is dissipated to heat energy in the internal combustion engine vehicles. However, modern internal combustion engine vehicles adopt engine stop-and-go during idle and also regenerative braking using the alternator.

### A. Propulsion Power Modeling

Electric Vehicle as a multi-domain Cyber-Physical System (CPS) consists of two major systems of electric motor and auxiliary system that are the main contributors to the power consumption [2], [38]–[40].

**Electric motors** are the key components of the propulsion system that generates force to propel the vehicle at a desired speed and acceleration. The electric motor consumes battery energy to produce driving force but can also behave as a generator when the applied torque becomes negative during deceleration. This regenerative braking system helps the electric vehicles achieve higher energy efficiency and extended driving range [41]–[43].

**Propulsion power** generated or consumed by the electric motor significantly influences the stored battery energy, the electric vehicle driving range, and the battery lifetime [44]–[46]. Hence, modeling, estimation, and optimization of the propulsion power are mandatory tools and methodologies to extend the driving range and battery lifetime.

*1) Physics Model:* Most of all, accurate propulsion power modeling is the basis of electric vehicle power estimation, runtime power management and design-time power optimization. Vehicle propulsion power modeling has been used for eco-driving research for internal combustion engine vehicles over

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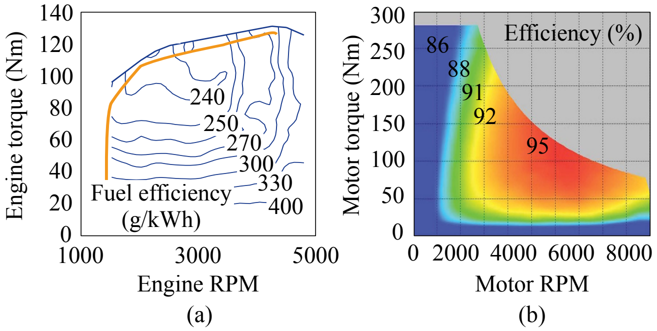


Fig. 1. A 1.4 liter GM Voltec Internal combustion engine efficiency map (a) and a Nissan Leaf 80kW electric motor efficiency map (b) [3], [4].

decades. An underlying propulsion power model is based on well-known physics equations. Such vehicle dynamics model basically takes into account the propulsion power applied to the tires.

$$P_{trac} = F\frac{ds}{dt} = Fv = (F_R + F_A + F_G + F_I + F_B)v \tag{1}$$

where $F_R$, $F_A$, $F_G$, $F_I$, and $F_B$ are the rolling resistance, aerodynamic resistance, gradient resistance, inertia resistance, and brake force provided by hydraulic brakes, respectively [1], [2]. This model applies to all type of propulsion systems as it assumes 100% efficiency of the propulsion system. As a result, this physics model does not explain electric-vehicle-specific power consumption behaviors such as electric traction motor characteristics, regenerative braking, battery efficiency, etc. Such simplification still can marginally estimate electric vehicle propulsion power but hardly use for propulsion power saving research.

One need to obtain the actual model coefficients for actual deployment of the power models of (1). Vehicle manufacturers often provide a part of model coefficients in the specification sheet such as the aerodynamic resistance as well as the curb weight, and tire manufactures commonly advertises the rolling resistance values of their products. Wind chamber experiments can also obtain unknown aerodynamic resistance values.

*2) Motor Efficiency:* The primary discrepancy between the electric vehicles and internal combustion engine vehicles can be explained by the source of the propulsion power: electric motors and internal combustion engines. Adding the electric motor characteristics to the physics model in (1) is able to accommodate electric powertrain characteristics.

Fig. 1(a) illustrates efficiency maps of a 1.4 liter GM Voltec engine and a Nissan Leaf 80kW motor. Electric vehicle efficiency is largely different from that of engine vehicles even under the same driving condition as the source of the traction force is a completely different characteristics, even if electric vehicles are subject to (1) as well. Electric motor efficiency varies by the motor type, motor revolution per minute (RPM) and torque. Consideration of traction device efficiency can significantly enhance the electric-vehicle-specific characteristics over (1) as shown as

$$\begin{aligned} P_{EV} &= \frac{P_{trac}}{\eta_{EV}} \\ \eta_{EV} &= \frac{P_{trac}}{P_{trac} + k_c T^2 + k_i \omega + k_w \omega^3 + C}, \end{aligned} \tag{2}$$

where $k_c$, $k_i$, $k_w$, $C$ are a copper loss, a iron and friction loss, a windage loss and constant loss, respectively [5]–[8].

*3) Drivetrain Efficiency:* Power consumption model in of (2) reflects efficiency of the electric motors. The actual electric vehicle propulsion efficiency is not only dependent on the traction motor but affected by the drivetrain loss in the gearbox, axle bearings, driveshaft, gearbox fluid, and many more, which varies by the vehicle speed, acceleration and motor torque. The actual model coefficients can be obtained from the motor companies, but this is not always the case. It is hard to rely on vehicle specification sheets to figure out drivetrain efficiency. Test run in various conditions helps collect range of power consumption data and obtain the model coefficients by a curve fitting method [9] with a high model fidelity of 1.7% overall cumulative energy consumption error [9]. A dynamometer test provides an isolated experimental environment [10] to obtain the actual efficiency of the traction motor combined with the drivetrain.

Consideration of accurate efficiency change of the traction motors and drivetrain loss can be highly nonlinear, and thus it is challenging to use mathematical equation models such as (1) and (2). Lookup tables are convenient to describe complicated power characteristics and also easy to implement a power simulator [10] while less convenient to use for systematic optimization.

More precise electric vehicle power modeling requires extensive power measurement and characterization. Use of production electric vehicles brings various limitations in non-intrusive power measurement. Fabrication of an electric vehicle [11] or electric vehicle conversion of a production internal combustion engine vehicle [12] efficiently overcomes the limitation in non-intrusive power measurement. The battery power should be measured together with the vehicle driving condition. Global positioning system (GPS) provides the location, altitude and thus road slopes. Such whitebox experiments efficiently isolate the propulsion power consumption from non-propulsion power consumption and give a lot of benefits in power modeling [11], [12]. It turns out that drivetrain loss in the electric vehicle is proportional to the square of the vehicle speed while the electric powertrain model only has a linear term of the speed as shown in (3) [11].

$$\begin{aligned} P_{EV-specific} &= \frac{P_{trac}}{\eta_{EV-specific}} \\ \eta_{EV-specific} &= \frac{P_{trac}}{P_{trac} + C_0 + C_1 v + C_2 v^2 + C_3 T^2} \end{aligned} \tag{3}$$

where $C_0$, $C_1$, $C_2$, and $C_3$ mean coefficients for constant loss, iron and friction losses, drivetrain loss, and copper loss, respectively. These methods guarantee a very high estimation accuracy (e.g., 2.89% maximum absolute error in [11]) for the target vehicle model. However, these models ensure limited accuracy when applied to general electric vehicles.

*4) Electric Vehicle Driving Range Estimation:* Most electric vehicle owners have range anxiety due to the limited driving range as well as inaccurate remaining range gauge on the instrument cluster. Depletion of the vehicle battery in the middle of a trip may bring a trouble equivalent to vehicle breakdown [11].

The electric vehicle power models of (1)-(3) require vehicle weight, acceleration, speed, and road slope as the input variables. It is impossible to know the actual values of the future vehicle acceleration and speed in real cases due to the uncertainty in the driving conditions. Such unknown factors can be modeled as probability density functions, and the resultant driving range estimation can also be represented probabilistically. This work models the uncertainty with a statistical speed profile [7].

Consideration of the battery characteristics is also attempted such as the state of charge versus the battery output voltage. For example, battery current keeps increasing as battery discharges even if the vehicle maintain a constant cruising speed on a flat road [5]. This work assumes that the vehicle speed should be decreased as the battery voltage decreases, but which is not in the real case because the battery should be cut off before it becomes fully discharged (over-discharge protection typically at 20% SoC) by the battery management system (BMS), and the motor driver should be able to maintain the same torque within the legal voltage range of the battery.

The fidelity of the power consumption model directly impacts on the range estimation accuracy [11]. The power model in (3) that considers the drivetrain efficiency exhibits less than 2.89% maximum absolute error in the power consumption, and thus between 0.05% to 4.39% in range estimation compared with real measurement [11]. On the other hand, the power models in (1) and (2), which consider only propulsion power and motor efficiency, obtain 6.85% and 9.33% maximum absolute error in the power consumption and up to 19.19% and 21.75% in range estimation, respectively.

### *B. Runtime Propulsion Power Optimization*

A large portion of previous work relies on the physics model in (1) or adding the motor efficiency in (2) to estimate electric vehicle power consumption. Therefore, derivation of the energy-optimal vehicle speed for a given road slope is often attempted with (1) or (2) [5]–[8], [12]. As mentioned in Section I, electric vehicles consume different amount of power and energy by the vehicle speed and acceleration due to the non-constant efficiency of the traction motor and the drivetrain even if the vehicles drive on the same route with the same payload. This inspires runtime propulsion power optimization, which is a similar concept of eco-driving of internal combustion engine vehicles [13]–[16]. However, the fundamental discrepancy in the electric powertrain from the engine powertrain makes the optimization policy largely different.

*1) Propulsion Power Optimization with a Constant Road Slope:* According to the electric vehicle power model in (3), propulsion power varies by the road slope as well as the vehicle speed, and thus the total energy consumption to finish the same distance of travel, i.e., the integration of the vehicle power over the driving time, forms a convex function of the vehicle speed for a given constant road slope as shown in Fig. 2. The shape of the convex function varies by the road slope, which implies that there exists the energy-optimal electric vehicle speed by a given road slope.

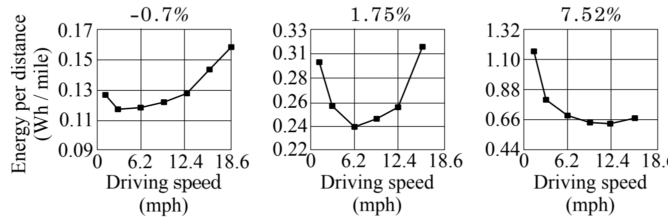


Fig. 2. Energy consumption versus electric vehicle speed on various road slopes.

It is very interesting to note that the energy-optimal speed increases by the road slope in the case of electric vehicles, i.e., electric vehicles should run faster on a steeper road to save energy. This inspires the minimum-energy speed planning over time (or distance) for a given driving mission: a route, a payload and a deadline, which is electric-vehicle-specific. Therefore, one of the simplest propulsion power optimization problem is defined as finding the energy-optimal vehicle speed planning (acceleration, cruising and deceleration) for a given constant road slope. Related previous work derives the energy-optimal vehicle speed planning without considering the traffic condition assuming a constant road slope [17], [18]. A trapezoidal driving, a combination of a constant acceleration, a constant speed cruising and a constant deceleration, is not an impractical driving method even in the real world with a smooth traffic flow, and a series of trapezoidal driving patten planning accommodates intersections with stop signs [17]. Fast computation is always beneficial for practical use to eventually accommodate traffic condition and route change guided by GPS navigation systems. A simplified analytical method that ignores aerodynamic resistance and motor efficiency help rapidly solve the energy-aware trapezoidal driving problem [18].

*2) Propulsion Power Optimization with a Variable Road Slope:* Many cities are located on hills as well as on flat lands. The energy-optimal trapezoidal driving may not work if the road slope varies before a single trapezoidal driving ends. The trapezoidal driving with a constant cruising speed is no longer energy optimal if the road slope changes. Consideration of the road slope change is crucial for freeway driving where there is no traffic signal nor intersection with stop signs.

The problem to solve the propulsion power optimization with a variable road slope is formulated as an optimal speed selection problem over distance as shown in Fig. 3(a). The X-axis and Y-axis in Fig. 3(b) denote the driving distance from the starting point and the driving speed, respectively. Each node indicates the driving speed at a given distance, and an edge between two nodes implies acceleration or deceleration during the distance step.

The energy-optimal speed profiles exhibit dynamically changing cruising speed taking the regenerative braking and speed limit into consideration as well. Previous work tackles

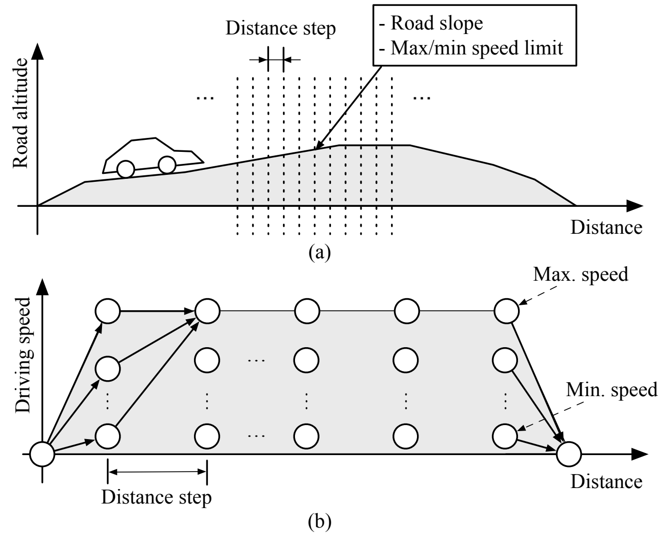


Fig. 3. Problem formulation for the propulsion power optimization with a variable road slope.

this problem without considering the traffic condition and stop signs by the use of analytical method [13], [14], dynamic programming [15], machine learning [16], and model predictive control [10]. Model predictive control (MPC) derives the optimal motor torque with the objective of a weighted sum of the energy consumption in every 400 m drive and the kinetic energy difference between the best constant speed and the derived speed [10]. These methods derives the energy-optimal speed profiles on a variable-slope road with a reasonable computational complexity but can hardly guarantee the deadline constraint.

Even if dynamic programming can hardly guarantee a hard deadline while minimizing the driving energy, making the cost function as a weighted average of the driving time and driving energy is able to consider the deadline in a certain degree [6], [9], [19], [20]. This method is useful for soft real-time system, which is the case of most common driving missions.

The dynamic programming with an weighting factor is formulated with follow:

$$\begin{aligned} &min \sum_{d=1}^{M}\sum_{v=1}^{N}\{w\Delta t x(d,v)P_{d,v}+(1-w)\Delta t\} \qquad (4)\\ &Subject\ to \sum_{v=1}^{N}x(d,v)=1 \quad \forall v\\ &\qquad x(d,v)=\{0,1\} \quad \forall d,v \end{aligned}$$

where $\Delta t$ is a driving time during the distance step, $d$ is a distance from the start point, $v$ is a speed at the distance, $P_{d,v}$ is a power consumption at a distance $d$ and a speed $v$, and w is weighting factor. $\Delta t$ is varied by the driving speed and the acceleration during the distance step.

A more explicit deadline awareness can be derived by iterative methods or semi-exhaustive heuristics that forms a multi-objective optimization problem such as genetic algorithm [8], [21]. However, these methods are subject to a very high computational complexity, which can be hardly used for online methods that are reactive to the traffic condition change and unexpected interruption by other cars or pedestrians.

*3) Propulsion Power Optimization Considering Traffic and Intersections:* The energy-optimal driving method introduced in the previous sections may not actually feasible in real traffic conditions. Safety is always first than energy saving, and thus heavy traffic often makes the vehicle slow down than the energy-optimal speed. Such traffic condition cannot be fully known a priori, and the derived energy-optimal driving method should be computed again whenever unexpected disturbance happens, which ends up with a local minimum energy consumption. Consideration of the traffic condition and traffic signal makes the energy-optimal driving more realistic [20], [22]–[27] even if such work is still based on strong assumptions. Such work is rather a high-level driving problem rather than electric vehicle-specific driving energy optimization.

Average speed of preceding vehicles on the same route marginally explains the distance between vehicles, which constrains the maximum possible target vehicle speed [20], [22]. Traffic signals are often controlled by a periodic schedule that mimics the energy-optimal driving [23]–[27].

A majority portion of intersection driving management is to optimize the throughput. There are intersection driving management work that explicitly optimize driving energy [26], [27] demonstrating 8% to 48% energy saving. Once again, such work does not perform electric-vehicle-specific driving energy optimization, and consideration of electric powertrain and regenerative braking may exhibit a large difference in the energy consumption.

*4) Propulsion Power Optimization Minimizing EV Life-Cycle Cost:* A cycle life of an EV battery is largely limited by its chemistry, but the charge/discharge behavior also significantly affects the cycle life [79]. From the EV owners' perspective, the total cost of ownership that includes the EV cost (battery chemistry and capacity), which is design-time optimization, electricity usage, which is runtime power management, and battery aging, which corresponds to the residual value and/or replacement cost, are equally important. The complete total cost of ownership optimization for a dedicated user is very complicated and yet is an open problem. However, there have been several research practices on battery aging and guidelines to extend the EV battery cycle life [36], [37]. Related work performes experiments to analyze the battery performance (capacity and allowable peak power) by cycle times under various driving conditions (*e.g.*, the temperature, driving profiles, etc.) Such work proposes guidelines under both non-operating condition and operating condition based on the experimental results.

### C. Design-Time Propulsion Power Optimization

It would be a more proactive energy saving if the energy optimality is considered at design time. Determination of the battery capacity is a really critical factor in electric vehicle unlike internal combustion engine vehicles questioning the gas tank size. The battery capacity directly impacts on the vehicle weight as well as the driving range, vehicle price and space

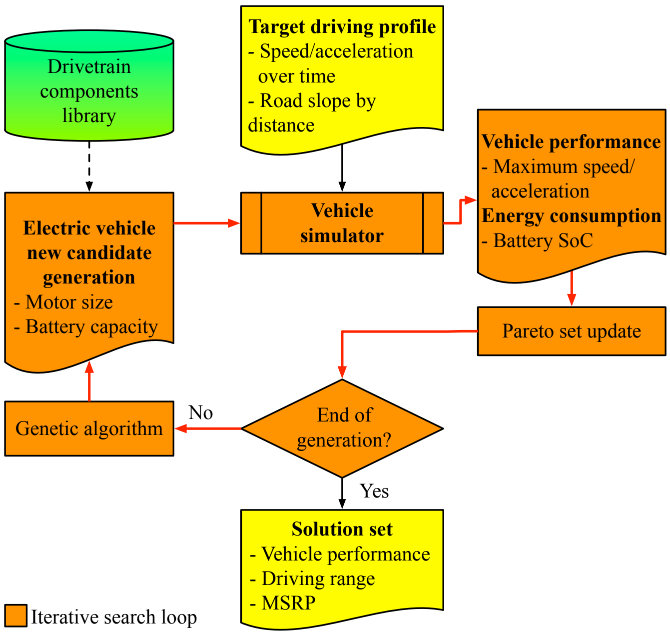


Fig. 4. Design-time propulsion power optimization dedicated to a driving mission.

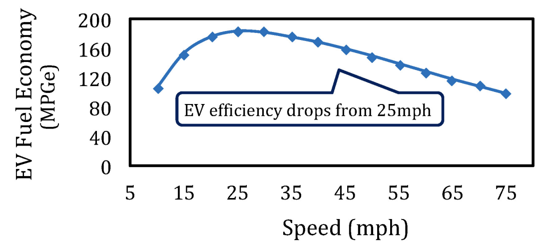


Fig. 5. Electric vehicle fuel economy for different driving speeds [46], [47].

utilization. As observed in Sections II-A and II-B, vehicle weight is a major variables that determines energy efficiency. Installation of a larger-capacity battery certainly increases the driving range but certainly decreases fuel efficiency (MPGe, mile per gallon gasoline equivalent.) Electric vehicles would better not carry an unnecessarily big battery pack while commuting in a short distance. A heavier battery pack also degrades the performance of the electric vehicles. On the other hand, a large capacity battery pack provides clear benefits such as a larger C rating (the Ah of the battery pack) that makes the battery efficiency higher, a lower battery temperature rise and a longer cyclelife. As a result, determination of the battery pack capacity must consider various aspects. To make a long story short, tailored specification of an electric vehicle dedicated to a particular operating scenario gives a huge opportunity to save energy consumption.

Design-time optimization requires extensive evaluation of the vehicle characteristics whenever a design variable is changed. It is not feasible to perform actual driving test during the design time. Automotive original equipment manufacturer (OEM) have been collecting range of data over decades and attempt to find a better empirical setup. Simulation environment can significantly reduces the design effort. Driving energy simulators evaluate the power consumption by changing the powertrain specification and estimate the vehicle performance and driving range as shown in Fig. 4. A vehicle simulator on a Matlab evaluates energy consumption by the motor, battery characteristics, gearbox, vehicle chassis, and so on [28], [29]. Related previous work optimizes the battery pack capacity for a given driving mission [30]. A supercapacitor and battery hybrid can prolong the battery lifetime [31]. The optimal reduction ratio of the traction motor to the wheels also increases the electric vehicle fuel efficiency [32]. Power rating of the traction motor, gear reduction ratio and the battery capacity should be jointly optimized. However, such design space is very big, and evaluation time complexity is huge. Genetic algorithm is a common way to solve such multi-objective optimization, and related work analyzes vehicle efficiency by the motor power rating and the battery capacity [33]. The design space becomes limited if the available components are in the limited number of libraries. Related work derives the optimal hybrid electric bus with 19 choices of diesel engine power rating, 19 choices of alternator capacities, 28 different size of traction motors, nine battery pack capacity variations, and seven gearbox reduction ratios [34]. Similar work attempts the best configuration of passenger vehicles and pickup trucks by the driving scenarios with four fuel cells, four motor power ratings, and eight battery pack capacities using Genetic algorithm [35].

## III. Driving Profile Modeling, Estimation, and Runtime Optimization

As mentioned in Section II, driving behavior significantly affects the propulsion power. Figs. 2 and 5 well demonstrate how driving speed affects the propulsion power and fuel economy [42]. The driving behavior can be modeled by the values of the driving speed, acceleration, and deceleration at each time instance of the driving route as the driving profile.

Therefore, modeling and estimation of the driving profile not only help in estimating the driving habits of the drivers, but also enable the designers and engineers to model, estimate, and later optimize the propulsion power in electric vehicles as described in Section II. On the other hand, adjusting and optimizing the driving profile itself is another effective approach to extending the driving range and battery lifetime [47].

### A. Modeling and Estimation

As described in Section II, electric motor of an electric vehicle is the main system contributing to the total power consumption and generation. One of the main factors deciding this propulsion power request, is the driving behavior. The driving behavior is modeled by the values of the driving speed, acceleration, and deceleration at each time instance of the driving route. This model that is called driving profile depends on various parameters of driving such as route conditions and the driver characteristics [38], [52].

The driving profile can be generated based on the data gathered from one driver while driving, in order to model a driver-specific driving profile; this can be achieved by monitoring multiple state variables of the electric vehicle at runtime using an On Board Diagnosis (OBD) device [53]. For instance, a biometric system may be incorporated into vehicle security in order to identify the driver. In other words, the amount of pressure a driver applies on the accelerator and brake pedals may be utilized in modeling their driving behavior and personal identification [54], [55]. Moreover, the anger and emotional aggressiveness of the driver may influence its driving behavior [56]–[58]. Hence, researchers attempt to model these factors that define the driving profile so that they can analyze their influence. Moreover, the safety and energy consumption of the vehicle are important factors influenced by the driving behavior that need to be predicted [58], [59].

On the other hand, the driving profile can also be generated based on the gathered data from all the drivers driving on a specific route, in order to model a route-specific driving profile. Certain navigation system databases like Google Maps [60] generate these models as part of the traffic information of their map databases by gathering data from all their clients or the sensors implemented in the city roads. Moreover, the data of this generic driving behavior can be used to generate driving test cycles. The automotive manufacturers may use these driving cycles to test and analyze the performance of their vehicles in terms of energy consumption and emissions [61], [62].

In summary, these driving profile models can be used for the purpose of personal identification, driver characteristics estimation, or estimation of the propulsion power by the electric motor. Later on, they can be adjusted and optimized for a specific driver or driving route in order to improve the performance of the electric vehicle in terms of battery lifetime, driving range, or even safety.

Typically, driving profile can be implemented simply as a matrix representing consecutive segments of the driving route ($\bar{s}$) (5). Each row in the matrix stores the information of the route condition and the corresponding driver reactions for each segment of the driving route.

$$\bar{s} = \begin{bmatrix} time & length & speed & acceleration & slope \\ t_1 & l_1 & v_1 & a_1 & \alpha_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ t_n & l_n & v_n & a_n & \alpha_n \end{bmatrix} \tag{5}$$

The information for each segment may contain the average time taken to drive the segment ($t_i$); segment length ($l_i$); average vehicle speed ($v_i$); average vehicle acceleration ($a_i$); and road slope ($\alpha_i$). The values for these elements can be retrieved based on the data gathered for the drivers and map databases as explained above [38], [47].

### B. Runtime Driving Management and Power Optimization

Driving management and route optimization have always been the most common problem of vehicles to improve the quality of transportation. Typically, driving management methodologies consider the driving distance and the driving time in order to find the fastest and shortest route to a specific destination [72]–[74]. Map databases are utilized to provide the required information for selecting the optimal route. More detailed driving profile modeling can enable the methodologies to optimize the driving routes considering other objectives such as energy consumption and the battery lifetime. For instance, driving profile model containing the segment information such as road slope and average speed will enable the driving management methodology to estimate the energy consumption of the electric motor at each segment. The routing algorithm can be implemented such that the weights for the edges of the graph are defined as same as the objective considered in the driving management as shown in Fig. 6 [75]–[77].

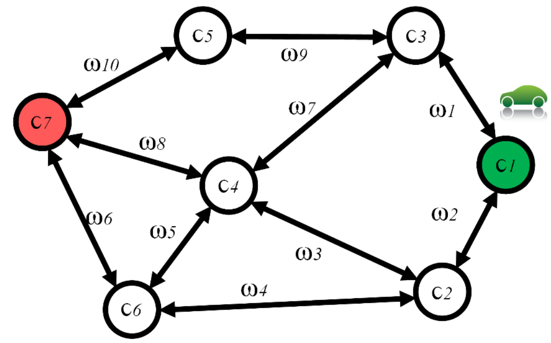


Fig. 6. Routing problem labeled with edge weights [47].

The results have shown that by sacrificing about 3 minutes of the driving time, a driving management can take a detailed driving profile and propulsion power modeling into account and reduce the energy consumption by 11.9% compared to the fastest route [47], [52].

Moreover, vehicles implement energy management methodologies that utilize the driving profile modeling to improve the driving range by reducing the energy consumption. For instance, the power split among the battery, combustion engine, and ultracapacitor is very important to the performance of the vehicle and its driving range. Predictive models of the driving profile are incorporated in the control to facilitate with the system estimation and control optimization [2], [44], [46], [69]–[71].

## IV. Non-Propulsion Power Modeling, Estimation, and Runtime Optimization

Besides electric motors, auxiliary systems in electric vehicles are the other major systems which influence its power consumption. Non-propulsion power requested by the auxiliary systems mostly depend on the functionality and objective of the system regardless of the driving behavior and profile. For instance, Heating, Ventilation, and Air Conditioning (HVAC) as an auxiliary system is responsible to maintain the cabin temperature in a comfort thermal range for the passengers [48]–[51].

Fig. 7 illustrates the details of three types of power consumption: 1) propulsion, 2) non-propulsion, and 3) accessory power consumption, for different temperatures in a Tesla Model S. The fraction of the HVAC power consumption (non-propulsion) mainly depends on the ambient temperature and the required comfort range. Although HVAC energy is

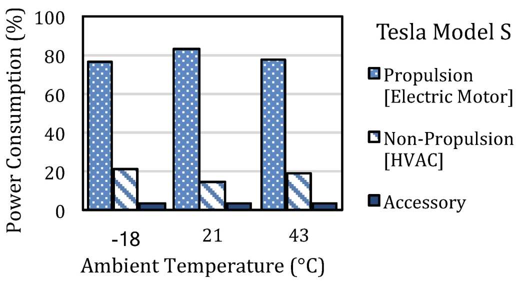


Fig. 7. Percentages of three types of power consumption in an electric vehicle for different ambient temperatures [38], [46].

proportional to the driving time, it is not sensitive to the detailed driving profile (speed and acceleration) unlike the electric motor. This characteristic shows that auxiliary systems have flexible load and power pattern. Hence, modeling and estimation of the auxiliary systems such as HVAC will enable the electric vehicle designers and engineers to further exploit this characteristic. Therefore, they will be able to adjust and optimize the non-propulsion power, e.g. HVAC power, in order to improve the operating parameters of the electric vehicles such as driving range and battery lifetime.

### A. Modeling and Estimation

Overall, the amount of non-propulsion power requested in an electric vehicle depends on the targeted auxiliary systems, their functioning components and the control process implemented to integrate and manage them. For instance, an HVAC is controlled by an automotive climate control in order to maintain the cabin temperature ($T_z$). The cabin temperature is influenced by the supply air ($T_s$) to the cabin and other thermal loads including the heat exchange with outside and the solar radiation. The air supply temperature is controlled by adjusting the temperature set points on heating and cooling coils. Moreover, variable air valves are utilized in a more complex HVAC in order to maintain the required thermal comfort for the passengers even in a multi-zone cabin. These systems utilize variable-speed fans and air ducts to provide the supply air to the zone(s).

Typically, the power consumption of the cooling ($P_c$) and heating coils ($P_h$) depends on the energy difference between their inlet and outlet air flows. Moreover, the power consumption of the variable-speed fans ($P_f$) is quadratically related to the air flow rate ($\dot{m}_z$). The thermodynamics of the cabin temperature considering all the control inputs and variables are modeled by energy balance differential equations. Hence, Ordinary Differential Equations (ODE) can be implemented to model and estimate the thermodynamic behavior of the HVAC system and its the instantaneous power consumption.

These models are typically used for evaluating and analyzing the performance of the auxiliary system – HVAC – and its influence on the whole vehicle. For instance, the researchers estimate the energy consumption of the HVAC system regarding different driving conditions like weather. This estimation is leveraged in order to predict the driving range of the vehicle and analyze how much HVAC influence this crucial parameter of the vehicle [58], [63], [64].

### B. Runtime Control Scheduling

During the operation of an electric vehicle, there are multiple control inputs which can be adjusted and optimized towards a certain objective. The controllers implemented are responsible to monitor the state variables and decide these control inputs. They may utilize the integrated modeling towards their estimation and optimization purpose. Previously in Sections II and III, we discussed how modeling of propulsion power and driving profile may help in optimizing the vehicle speed, acceleration, driving route, and power split.

Auxiliary systems in electric vehicles implement control algorithms responsible for scheduling control actions in their systems. The decisions made by the controller will influence the non-propulsion power requested by the auxiliary systems. For instance, in an auxiliary system like HVAC, an automotive climate control basically senses the cabin temperature and weather and decides how hot and cool the supply air temperature should be, given the model of the cabin and HVAC [65]–[68].

The automotive climate control adjusts the control inputs into the HVAC in order to maintain the cabin temperature around a certain target and within a comfort range. The climate control may be implemented using an MPC or a rule-based control. The controller may leverage the HVAC dynamic and non-propulsion power models to estimate the state, auxiliary, and output variables according to specific control inputs for a certain prediction horizon in the future. The controller utilizes an optimizer to adjust the control inputs such as heating and cooling coil temperature set points and the fan speed of the prediction horizon while considering the constraints. The controller may be responsible to minimize an objective or cost function.

An automotive climate control may only consider the cabin temperature as the objective [65]–[68]. However, the power consumption of the HVAC (non-propulsion) and the electric motor (propulsion) may be considered as well in order to reduce the influence on the electric vehicle energy and battery capacity loss [46], [64]. Therefore, depending on the details of the modeling, the cost function may include the 1) cabin temperature variation, 2) HVAC energy consumption, and 3) battery capacity loss. Moreover, there are certain constraints on the control inputs and state variables which should be satisfied during the optimization and control process.

Therefore, the control scheduling of the auxiliary systems may reduce the battery stress, improve the driving range, and the battery lifetime by adjusting the non-propulsion power such that it compensates for the propulsion power or the quality of the system. It has been shown that an MPC-based methodology given the models is able to minimize the non-propulsion power on average 39% compared to the fuzzy-based methodology which minimizes by 6% [46], [67], [78].

## V. Battery Systems for Electric Vehicles

Battery systems are an important part of electric vehicles. The main research areas in battery system are modeling, simulation, estimation and optimization. In the following, literature survey of battery systems for electric vehicles is presented.

### A. Modeling

Rechargeable batteries that offer high energy and power density and relative safety are the choice for many applications from consumer electronics to electric vehicles. One example of such batteries are Lithium-ion batteries. Modeling the cycle and calendar life of such batteries is needed to set expectations of reliable product performance. Generally, there are two types of models to predict the battery life [79]. One type of models describe chemistry of the cell [80]. These models, with the help of extensive computation facilities, provide time and temperature effects accurately but do not match with cycle life test data. Such models are best suited for optimization of the physical design aspects of electrodes and electrolyte [90]. The other type is empirical models [81] that fit the test data to equivalent circuit models using power law relationships. These models have limited range of parameters and require extensive testing of each type of cells.

A simple battery model consists of an ideal battery with an open circuit voltage and and a constant internal series resistance. A new battery model based on simple battery model was proposed in [82]. In this battery model, SoC (State of Charge) of the battery is considered as well by making the internal resistance variable. Another commonly used model is the Thevenin battery model in Fig. 8, which consists of an ideal no-load battery voltage ($E_o$), internal resistance ($R$), capacitance ($C_o$) and overvoltage resistance ($R_o$) [137]. $C_o$ represents the capacitance of the parallel plates and $R_o$ represents the non-linear resistance contributed by the contact resistance of plate to electrolyte. The main disadvantage of the Thevenin battery model is that all the elements are assumed to be constant, but in fact all the values are functions of battery conditions.

An empirical mathematical model is developed in [83], [84]. The improvement of this model is to account for the nonlinear characteristic of both the open circuit voltage and internal resistance. A sophisticated and accurate dynamic model for simulation purpose was proposed in [85]. This model includes electrolyte reaction, Ohmic effect and leakage capacitance as well as the self discharge current. The drawbacks of this model include longer time for computation because of its higher order and complicated modeling procedure that involves a lot of empirical data. Another battery model is called over-current battery model as described in [86]. It has a variable current source, a variable voltage source, a variable resistor, and a capacitor. This model provides a good representation of both variable internal drop in the battery and changes in the output voltage due to the SoC. However, one of its drawbacks is that too many parameters are required. A model described in [87], [88] considers most nonlinear battery element characteristics both during charging and discharging as well as their dependence on the SoC of the battery. All the elements included in this model are functions of the open-circuit voltage of a battery, which in turn relates to state of charge [89].

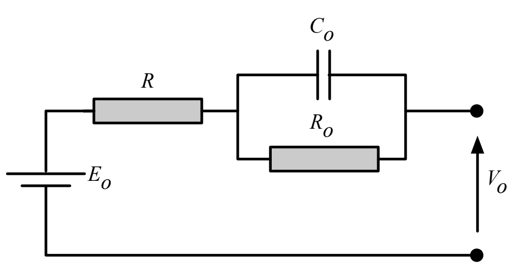


Fig. 8. Thevenin battery model [137].

The model in [91] is capable of predicting run time and I-V performance, but is not accurate for the transient response to short-duration loads. As a result, it does not predict accurately the SoC throughout drive cycles for electric-vehicle-related simulations [92]. A model proposed in [92] describes accurate determination of the discharge capacity, which is a function of the discharge rate, temperature, cycle number, and a rate factor that accounts for a decrease in capacity due to unwanted side reactions as the current increases. This model can also predicts SoC, terminal voltage and power losses of various batteries for electric vehicles. Along with predicting the battery behavior accurately, this model can be used for simulation as well.

### B. Simulation

Simulation with an accurate battery model is able to analyze complex phenomena. Average ratings can be derived from steady-state operation and characteristics of the system, but peak ratings can only be estimated from the steady state results and are often inadequate. A detailed model is appropriate for short-term analysis and supplements the long-term capabilities of a steady-state model as described in [95], [96]. In order to better understand losses, thermal characteristics, and durability of various electric vehicle batteries, a dynamic simulator is a key tool. Estimates of conducting losses in power electronics devices, batteries, supercapacitors, and other components can be supported directly with a dynamic model. Dynamic models are needed to make lower-level comparisons among subsystems and support subsystem design. Steady-state simulation tools for the design and analysis of hybrid electric automotives have been developed in recent years and support comparisons over long drive cycles. In the past, dynamic simulation models have focused mainly on the analysis of control strategies [94]. A dynamic simulator in [93] offers a more detailed look, based on dynamic equations of each subcomponent (the engine, battery, inverter, motor, and transmission) on microsecond time scales.

Several simulation systems have been developed to describe the operation of hybrid electric power trains such simple electric vehicle simulation (SIMPLEV) from the DOE's Idaho National Laboratory [97]. Simulation programs include MARVEL from Argonne National Laboratory [101], CarSim from AeroVironment Inc., JANUS from Durham University [102], Vehicle Mission Simulator [103], and others [104], [105]. A simulation model (ELPH) is used to study the viability of an electrically peaking control scheme and to determine the applicability of computer modeling to electric vehicle design [98]. V-Elph [99], [100] is a system-level modeling, simulation, and analysis package. This package uses Matlab/Simulink to study issues related to electric vehicle and hybrid electric vehicle design such as energy efficiency, fuel economy, and vehicle emissions. V-Elph facilitates in-depth study of power plant configurations, component sizing, energy management strategies, and the optimization of important component parameters for several types of hybrid or electric configuration or energy management strategies with visual programming techniques, allowing the user to quickly change architectures, parameters, and to view output data graphically [28].

### C. Estimation

Automotive Lithium-ion batteries have high capacity and large serial parallel numbers, which, coupled with the problems such as safety, durability, uniformity and cost, imposes limitations on the wide application of lithium-ion batteries in vehicles. Lithium-ion batteries must operate within the safe and reliable operating area, which is restricted by temperature and voltage windows. Exceeding the restrictions of these windows will lead to rapid attenuation of battery performance and even result in safety problems [106]. The accommodation of such operating conditions requires that a management system has accurate knowledge of many factors e.g. the SoC to facilitate safe and efficient operation. Failure to control SoC, which may lead to under- or over-charging conditions, can degrade the ability of the pack to source/sink subsequent power transients [107].

A variety of techniques have been proposed to measure or monitor the SoC of a cell or battery, each having its relative merits [108]. Coulomb counting or current integration is, at present, the most commonly used technique, requiring dynamic measurement of the cell/battery current, the time integral of which is considered to provide a direct indication of SoC [109].

Due to complexity of electrochemical processes in batteries and noise in sensors, many sophisticated algorithms have been proposed for efficient battery monitoring, such as estimation of SoC [110]. An earlier work which uses voltage as the basis of SoC estimation is presented in [113]. Though this work deals with complexities such as hysteresis, it is difficult to estimate SoC for some battery types such as Nickel-metal hybrid. A fuzzy logic approach for SoC estimation is presented in [114]. This approach requires training data, which is challenging because of changing properties in different conditions. A complex neural-network-based approach is presented in [115], but it is restricted to lead acid batteries and requires complex network design and computation.

A hybrid neural-network and genetic-algorithm based approach of SoC estimation of series connected modules (battery cells) is discussed in [116]. Despite the promising result, the proposed method is relatively complex and has high computational cost. In [117], a complicated mathematical model has been devised, specifically for lead acid batteries, which can predict the SoC and remaining operation time with up to 10% error. A nonlinear estimation method based on the sliding mode observer is presented in [118]. This work also discusses the parameters of the battery model through different tests. A novel algorithm is presented in [119], which combines the weighted sum of complex voltage based methods and Coulomb counting techniques. An earlier method based on Kalman filter is presented in [120]–[123]. In addition to a few similar methods, a famous estimation algorithm based on Extended Kalman Filter is proposed in [124]–[129] and has shown promising results. The method proposed in [130] can robustly estimate SoC by using simple but accurate battery models employing a conservative filtering technique. The $H_\infty$ filter is solved optimally by formulating it as a Linear Matrix Inequality problem. The separation of computation (calculation of gain once and iterative implementation of estimator) enables the proposed method to be implemented on embedded controllers without compromising real-time operation requirements.

SoH (state of Health) is a quantifying estimation that reflects the general condition of a battery and its ability to deliver the specified performance compared with a fresh battery. Battery capacity (i.e., the energy storage capacity) has long been the target of researchers as the definitive battery SoH indicator [111]. In general, a lithium battery is deemed to fail when its capacity fades by 20 % of the rated value [112].

### D. Optimization

One of the problems for electric vehicle designers is that energy and power density need to be carefully balanced. Heavy batteries increase the vehicle's range and light batteries increase the power-to-weight ratio, enabling the electric vehicle to achieve better acceleration. More batteries, however, increase the cost of the vehicle design.

Electric vehicles do have quick acceleration, due to the high torque of the electric motor. Currently nickel metal hydride (NiMH) and Lithium-ion are the common, though research continues into new battery chemistries, such as nanophosphate cathodes, to allow for high discharge rates and higher performance. The discharge rate for batteries contributes to not only acceleration rates, but also how quickly the batteries will be charged. The higher the rate, the more energy is lost through heat. Supercapacitors are available as alternative components. They have high charge and discharge rates, resulting in lower losses but these benefits can be outweighed by their low energy density [131].

The charging management concepts can also be divided into centralized and decentralized approaches [132]. The decentralized approaches let the electric vehicles optimize its charging behavior based on, for example, a price signal broadcast. The drawback of this approach is that the electric vehicle needs to collect and store the trip history. If the electric vehicles should coordinate their charging, for example to include distribution grid constraints, the need for V2V (Vehicle to vehicle) communication is high.

The centralized approaches focus on a centralized unit that directly controls the charging of electric vehicles. Additional study on forecasting and managing electric vehicle charging can be found in [133], [134]. A novel method for optimization is presented by [135] which describes the method for planing the charging of electric vehicles with electric grid constraints including voltage and power. This method provides an individual charging plan for each vehicle, which helps in avoiding the congestion on distribution grids. Using quadratic approximation approaches to optimize the behavior electrical vehicle battery, the goals of minimizing charging costs, achieving satisfactory state of energy levels and optimal power balancing have been achieved [136].

## VI. Energy Harvesting for Electric Vehicles

Energy harvesting refers to harnessing energy from the environment or other sources (e.g. solar, thermal energy, friction etc.) and converting it to electrical energy. In electric vehicles, energy harvesting works as an important energy resource, which can save a lot of electric energy and thus can extend the range of electric vehicles with the same charging time. Nowadays, a lot of electric vehicles are powered by harvested energy or hybrid energy including harvested energy, such as solar energy, wind energy, and energies brought by vehicle shock/vibration and brakes. In the following, we survey different energy harvesting techniques in electric vehicles and summarize the research work on different sources of harvested energies on electric vehicles.

### A. Energy Sources

*1) Solar:* As one of the most important renewable energy sources, solar energy is positioned to reduce the use of natural gas and coal for electricity generation and to provide electricity for the plug-in electric vehicle market [155]. Abundant sunlight makes it perfect to be used as an alternative energy on electric hybrid vehicles [146], [186]. The annual potential of solar energy is several times larger than the total energy consumption in the world.

The most common mechanism to harvest solar energy is directly converting the light into direct current electricity via the photovoltaic effect. Fig. 9 shows the system circuit of a photovoltaic (PV) powered electric vehicle, which consists of a PV array and peripheral charging regulation circuitry [191][166]. A PV array consists of a number of series-connected PV cell groups where each PV group consists of (potentially a different number of) PV cells connected in parallel. The PV array are mounted on the roof panel, engine hood, trunk, and door panels of the electric vehicles. Conventional electric vehicles are equipped with battery packs as the energy storage system, connected to the traction motor via the generator charger. The PV-powered electric vehicle also has an add-on PV system that consists of a PV array and a PV charger connecting the PV array to battery packs. The generator charger and PV charger can simultaneously charge battery packs. Maximum power point tracking (MPPT) techniques are integrated with the PV charger, which are employed in photovoltaic systems to make full utilization of PV array for large output power [142], [170], [174]. Therefore, the PV charger can set the optimal operating point for the PV array. There are three main issues for solar energy harvesting.

First, since the PV cell array is installed on different parts of a vehicle body such as the engine hood, door panels, and the roof panel, and the system suffers from non-uniformity of the solar irradiance and partial shading phenomenon. Partial shading of PV arrays is one of the hottest problem in the field of solar photovoltaic. It exhibits multiple peaks in the

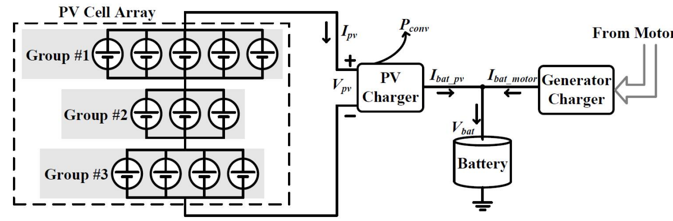


Fig. 9. Circuit of a PV system on a electric vehicle [191].

PV and thus reduces the overall output power [181]. As a result, the modules have to be reconfigured to get a maximum power output. Many previous work [143], [166], [187], [191] presented dynamic PV array reconfiguration techniques to produce the near-optimal reconfiguration of the PV array on the electric vehicle. For these work, the goal is to maximize the PV system output power under any solar irradiance and temperature distribution on the PV array. A model is developed in [189] to describe the effects of solar panels area and position, vehicle dimensions and propulsion system components on vehicle performance, and further exploited it for optimization.

Second, the difference in energy demand for DC motor impacts the lifetime of the battery. When the car is decelerating, energy demand for the DC motor is very less and voltage drop of battery is negligible. However, when the car is accelerating, climbing slope or starting, the motor will cause a large current impulse, which may lead to large voltage drop on the battery. This will affect power quality of DC source and lifetime of battery. In order to avoid this, [139], [160], [190] proposed to employs a super capacitor. When the car is decelerating, super capacitor will charge up to its rated voltage. Multi-port converter interfacing a photovoltaic array, battery and a DC load is proposed. It is composed of a two uni-directional DC port for interfacing photovoltaic array and DC load, and a bi-directional DC port for interfacing battery. The capacitor which is connected to the lead acid battery will charge at off peak hours and discharge during the acceleration time of the car. The control strategy of bi-directional converter is proposed, which operates at three operation modes: charge battery, discharge battery, and shut-down. The advantage is better protection and more efficient control on charge/discharge of the battery.

The third issue of solar vehicle is to achieve the the routing request in bounded time [141], [150], [153], [173]. Particle swarm optimization is adopted to make sure that the vehicle reaches the destination within the user defined delay [150]. The energy consumption ratio in [141] is introduced to measure the efficiency of the solar vehicle which is denoted as arrival ratio divided by energy consumption. The aim is to achieve a high energy consumption ratio for the time-bounded routing request. The work [153] proposed to optimally plan the speed on different road segments and thus balancing energy harvesting and consumption With the consideration of the solar illumination and the traffic flow, a suitable speed is predicted for the solar vehicle to have the minimum energy using in moving.

In addition, by using nano-materials the incident radiation

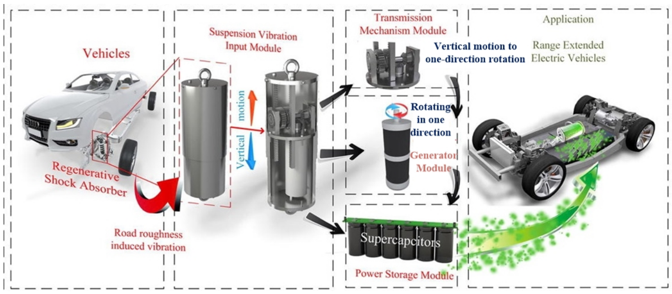


Fig. 10. Regenerative shock energy converted into electricity [197].

can be increased by 9 times [138] while the efficiency of the solar collector is 10% higher compared to that of a conventional flat plate solar collector.

The amount of power generated by PVs is maximum 200 W per square meter under 1 kW input solar power. On the other hands, EV power consumption is average 16 kW when Tesla Model S drives at 55 mph. Therefore, a simple calculation shows that PV power generation is way shorter than the EV power consumption. However, PV energy harvesting is still useful when the vehicle is parked for hours. PV panels on the EV can harvest driving energy for significant if the EV is driven for commute in the morning and evening while it is parked at the non-covered parking lot during the whole daytime.

*2) Regenerative shock absorbers:* When an electric vehicles move in the road, the suspension power of the conventional shock absorbers are normally dissipated through friction and heat. However, these wasted energy in a vehicle's shock absorber can be collected and converted to an alternative electric energy through energy regenerative shock absorber, as shown in Fig. 10.

Fundamental research has examined and analyzed the feasibility of harvesting energy from the shock absorber since the 1980s [184]. The regenerative shock absorber was proposed to harvest the kinetic energy dissipated by the suspension vibration in the shock absorber. In [184], the authors described and analyzed how energy lost in a car shock absorber corresponding to different vehicles' speed and road roughness. Recent studies further uncovered the potential of energy harvesting from the shock absorber [161], [199]. The work [199] made a significant improvement in the energy harvesting and ride comfort of regenerative vehicle suspensions over existing techniques. The authors presented a regenerative shock absorber and estimated a power range of 100∼400 W at 100 km/h depending on the road profile. In [161] the authors proposed an analytical methodology based on ground tire interface analysis and ride comfort cost function for an energy-regenerative suspension design. This research work aimed to achieve optimal performance and ride comfort and derive the closed-form solutions of the performance metrics for an energy-regenerative suspension. Among these initial theoretic studies, the shock absorber was transformed into an energy harvesting device from an energy dissipating device. Possible noise and heat in the conventional working progress are eliminated, which is environmentally friendly and lifetime extending.

With respect to long-term evolution and development, regenerative shock absorbers can be classified into three categories based on their working principles: electromagnetic, hydraulic and mechanical designs.

The first category directly uses an electromagnetic method to generate the electric power. The methods include linear [157], [165], [192], [194], [198] and rotary schemes [158], [171]. A linear electromagnetic regenerative shock absorber converts the kinetic energy of vertical oscillations into electricity by electromagnetic induction. The structure of linear schemes is simple and kinetic energy is converted directly. Unlike normal linear movement damper, rotary damper rotates by the upper arm of suspension when tire move up and down. This structure has high efficiency which can reach 90% for both driving and back driving but needs to change suspension structure largely which in turn will have influence on the handling and stability performance.

For the second category, hydraulic regenerative shock absorbers can harvest the vibration energy and convert this energy into electricity by employing oscillatory motion to drive the power generator. They utilized commercial DC/AC motors as generators and focused on various methods to drive these generators. A number of studies reformed the existing hydraulic shock absorber and utilized the oil in the shock absorber to flow into a side oil circuit [154], [196]. They normally use the flowing fluid to drive a hydraulic motor, which is connected in parallel to a DC/AC generator. Check valves are also used to ensure unidirectional fluid flow and unidirectional rotation of the hydraulic motor.

The third category is mechanical design, which is developed rapidly because of a greater efficiency and average power. In previous studies [140], [158], [176], [183], ball screws have been used for the transmission of regenerative shock absorbers for the sake of good stiffness and transmitting efficiency. An energy regenerative suspension is designed and improved using an algebraic screw linkage in [176], [183]. A hexagon linkage was used in the initial design, and a two-leg linkage was presented in latter schemes. The work [156] compared different electromagnetic shock absorbers and found that rotary schemes had large power compared with the linear schemes in bench tests. The results also indicated that rack and gears have the potential to drive a larger DC/AC motor to achieve greater power density. In [167], the authors analyzed and modeled an equivalent circuit for an electromagnetic regenerative shock absorber using a rack and gears. This model assisted the evaluation and optimization of the rack-and-gears schemes. Rack-and-gears regenerative shock absorbers based on a mechanical design were rapidly developed because of their high efficiency and average power [168], [169].

*3) Regenerative braking:* Regenerative braking is that the kinetic energy from a moving car generates electricity back to the battery when a vehicle is in coasting and braking modes as shown in Fig. 11. With regenerative braking technique, it is shown that electric vehicles can increase the driving distance up to 15% with respect to electric vehicles without the regenerative braking system.

According to different ways to capture the energy gener-

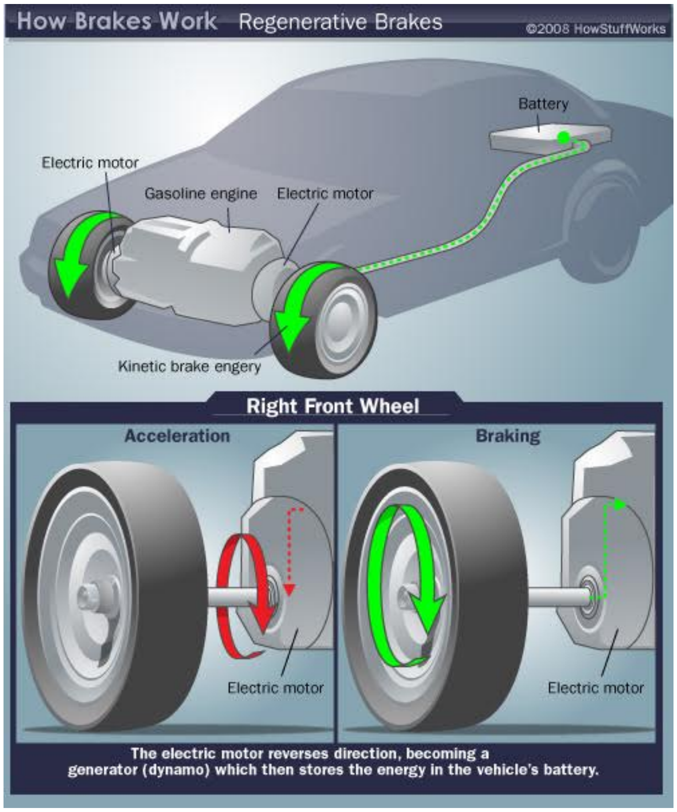


Fig. 11. Regenerative brakes [200].

ated by regenerative braking, the-state-of-the-art regenerative braking systems can be clarified into the following four types. First, the electricity generated is stored directly into batteries. Unfortunately, due to frequent charging, the lifetime of batteries will be decreased [148], [172]. Second, instead of directly charging to battery, ultracapacitors/supercapacitors are used to store the energy from regenerative braking [147], [163] Besides, ultracapacitors are the options with higher power densities compared to batteries. The above two kinds of systems can capture and return around 50% of the energy lost in braking [175], [188].

Third, the break energy can be stored by hydraulic motors into a small canister through compressed air. When you hit the brakes, this system engages a pump which forces compressed air into a tank. This converts the mechanical energy of motion into elastic energy in the gas. These systems can capture and return around 70% of the energy lost in braking [162], [182].

The last way is that, energy can also be stored in Flywheel energy system (FES) as rotating energy. When you hit the brakes, this system transfers the mechanical energy of motion into electricity, which is then used to speed up the flywheel [152], [159], [193]. These systems can capture and return around 70% of the energy lost in braking [175].

## VII. Impact of Electric Vehicles on Power Grid

Electric vehicles are connected to the power grid via AC charger or fast AC or DC chargers. The power capacity of electric vehicle charging station can be as high to 1.2 kW to 240 kW [201]. The random charging activities of numerous electric vehicles significantly stress the distribution system causing sever voltage fluctuations, degraded efficiency and economy [202], [203]. However, electric vehicles are also able to feed power back to the Grid (regeneration). If properly designed, electric vehicles can provide ancillary services to support the supply network as a distributed storage unit [204], [205]. In power systems, this two-way communication between the utility and the power supplier is also called the Smart Grid [206].

In this section, literature reviews of electric vehicles integration and impact on power grid are presented, including electric vehicle charging load model, impact of electric vehicles charging and discharging on the power grid.

### A. Electric vehicle charging load model

Electric vehicles can be considered as active loads connected to the power grid in the charging mode. Therefore, an accurate model of the charging load is critical to the design of the power networks. The properties of batteries and user behaviors are two key factors that influence the charging load modeling of electric vehicles. The modeling of batteries are presented in Section V. In the following we summarize the impact of user behaviors on the charging load modeling.

Previous work [207] analyzed naturalistic driving data and vehicle resting patterns in the context of electric vehicles design and impact on the power grid. Driving schedules were utilized as input through simulations to determine the vehicles energy use per trip and per day. These driving behaviors are then used to make predictions of the possible charging schedules and locations. As data collection is mandatory to ensure the solution fidelity, related work [208] recorded vehicle usage data for 76 vehicles in a one–year period in the city of Winnipeg, Canada, and used this data to predict electric vehicles charging profiles and electrical range reliability. In this work, a stochastic charging profile prediction model is proposed base on the vehicle usage data. In [209], a preliminary road traffic simulation is conducted to determine the typical range which electric vehicle of a particular technology will achieve under consideration of everyday traffic. By utilizing the exponential distribution, they built the charging load model of electric vehicles.

### B. Impact of electric vehicles charging on the power grid

*1) Modeling:* Current research on the impact of massive integration of electric vehicles in power systems is generally focused on the development of business models, integration into the network, and impact on power system operation. These models can be broadly divided into two types: hourly time-series model and longterm large-scale model [210]. The hourly time-series model is only based on hourly historical data of electric supply and demand as well as charging data of electric vehicles to decide whether the power system meet the needs of electricity supply in the short time. The long-term large-scale model run on regional or national scale over decades, with consideration on the mix of various constraints (economic, political, etc.) to build a optimized model. Current models of electric vehicles charging are mostly hourly time-series model due to its simplicity. Previous work [211] established an hourly time-series model, which used a quadratic programming method based on stochastic approach. Compared with classical dynamic programming model, the results show that quadratic and dynamic programming model are giving the same results but quadratic programming is faster and more accurate. A mid-term model simulates hourly power system operation in the Spanish power system is proposed in [212]. This model includes electric vehicles in the unit commitment and represents in detail mobility and connection patterns, and achieves more realistic estimation of electric vehicle economic and other factors. Some researchers believe the future research need to balance the calculation and accuracy of the actual situation [210]. Related work also indicates future research should include more analysis and calculation of randomness and grid reliability index to the model [213].

*2) Simulation:* The integration of electric vehicles in power systems has adverse impact on the distribution grid as extra loads are added by the electric vehicles. A lot of related research [201], [214]–[220] has been done to estimate whether existing of planned power supply capacity can accommodate electric vehicles charging load growth. An observation on the usage of electric vehicles in Virginia and the Carolinas in the U.S. found that peak loads would increase under a simple charging strategy, requiring extra investment in generation and transmission capacity [214].

Electric vehicle charging can also cause the power quality issues, including line loss increase, life span of distribution transformers decline, harmonic and fault current increase [221]–[225]. These and other more technique issues are reviewed in [213]. Electric vehicle charging in a disorderly manner over the distribution network would lead to node voltage offset and the damage of network lines if the owner does not make any restrictions [226]. The effect of electric vehicles on residential distribution transformers is also reported in [227]. Results show that the effects are negligible when electric vehicles are at low penetrations, but serious losses arise with increasing vehicle numbers. A study on UK distribution systems [228] indicates that large number of electric vehicles lead to voltage limit violations, transformer overloads and increased line losses.

Recent studies show that the current U.S. generation infrastructure could only support 70% of the existing U.S. electric vehicles [229] if the charging schedule are well coordinated. Otherwise, serious mismatch can arise between the electricity supply and consumption [214]. With the growth of penetration levels of electric vehicles, the distribution system could be further impacted, including increased system peak load, losses, and decreases in voltage and system load factor [230], [231].

*3) Optimization:* To mitigate the impacts of electric vehicle charging on the power grid, additional investment on generating electricity and transmission capacity are needed [201]. It is also important to carry out intelligent control safely and effectively for charging behavior of electric vehicles to increase grid reliability [228]. Other works target at optimization of the charging plan instead of investment on additional electricity capacity. Previous studies have demonstrated that existing capacity can accommodate the overnight loads of a modest penetration (up to 20%) of electric vehicles [232]. Related work show that employment of smart charging plans would achieve a flat overnight load and further optimize overall charging at high electric vehicles penetration [217], [233]. Elaborated optimal charging algorithms can coordinate charging of electric vehicles so that the distribution system losses could be minimized. [234] developed three optimal charging algorithms. The results also provides additional benefits of reduced computation time and problem convexity when using load factor or load variance as the objective function rather than system losses.

TABLE I
PHEV CHARGING SCENARIOS (PHEV: PLUG-IN ELECTRIC VEHICLES; CHP: COMBINED HEAT AND POWER.) [213], [235]

| PHEV/CHP Penetration | Grid-To-Vehicle | Vehicle-to-Grid |
|---|---|---|
| 10 | 10pm-6am | 6am-10pm |
| 10 | 9pm-9am | 9am-9pm |
| 10 | Continuous | Continuous |
| 30 | 10pm-6am | 6am-10pm |
| 30 | 9pm-9am | 9am-9pm |
| 30 | Continuous | Continuous |

### C. Impact of electric vehicles discharging on the power grid

Electric vehicles connected into power grid can also play a role in regulating power supply and demand balance. As show in Table I [213], [235], we can charge electric vehicles when grid load is low. When the power grid load is peak, the electric vehicles connected into network can be viewed as a distributed energy storage unit, which contribute electricity back to the grid system. This bi-direction interaction of electric vehicles and the grid is called vehicle-to-grid (V2G) [236], [237]. Moreover, V2G are able to harvest energy form large-scale intermittent renewable energy sources (wind, solar, etc.) as discussed in Section V, this would obviously impact the distribution grid as V2G enable electric vehicles could actually act as distributed generators connected to the power grid. The fundamental calculation of costs and power that are associated with V2G technology is described in [236]. Based on these basic cost and power models, [238]–[240] further discussed the characteristics, benefits, flaws, economics, and technical specifications of V2G. Moreover, detailed V2G implementation steps to assist the transition of V2G technology are described in [237].

The V2G implementation involves frequent and intensive charging and discharging processes. To tackle such complex charge exchange between the power grid and the EVs, the unidirectional spinning reserve V2G algorithm is proposed [243] to adjust the EV charging rate according to a Preference Operating Point (POP), where the minimal preliminary investment and EV batteries degradation can be achieved. Later bidirectional V2G technologies [244]–[246] simultaneously utilize the Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) operations in a more flexible way addressing the requirements of both the power grid and EVs. Meanwhile, various V2G scheduling strategies [234], [247], [248] aim at minimizing the power grid load variance. In general, one of the most commonly used mitigations to reduce power grid operation loss while accommodating a large size of the EVs penetration is to shift this extra load to a valley period or to optimize the available power using the coordinated charging schemes [249]. On the other hand, compared with classical power plants, renewable energy sources have higher power energy fluctuation and intermittent. However, [241] indicates the wind profile in New York matches electric vehicle charging need very well: the electric vehicles could be charged when power supplied by wind power is the greatest and V2G technology could be use to feedback energy to the grid by wind turbines. Related work [242] investigated the potential role of electric vehicles in an electricity network with a high contribution from variable generation such as wind power. The simulation models 1000 individual vehicle entities to represent the behavior of larger numbers of vehicles. A stochastic trip generation profile is used to generate realistic journey characteristics. Finally, experimental results show that the electric vehicles connected to the grid and discharge make up for intermittent of wind generate power, also bring the owners with a certain economic benefits.

## VIII. Conclusion

Electric vehicles are being rapidly penetrating the automotive market as they are well accordance with semiconductor and computer system evolution as well as environmental friendliness. However, their energy consumption is yet comparable to that of internal combustion engine vehicles while conventional approaches can hardly achieve further significant amount of energy saving. This work is to inspire range of system-level energy saving research providing comprehensive survey on propulsion power, energy-efficient routes, non-propulsion power, vehicle batteries, energy harvesting, power grids for electric vehicles.

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