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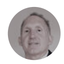

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A Review and Outlook of Energy Consumption Estimation Models for Electric Vehicles

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Abstract
Electric vehicles (EVs) are critical to the transition to a low-carbon transportation system. The successful adoption of EVs heavily depends on energy consumption models that can accurately and reliably estimate electricity consumption. This paper reviews the state-of-the-art of EV energy consumption models, aiming to provide guidance for future development of EV applications. We summarize influential variables of EV energy consumption into four categories: vehicle component, vehicle dynamics, traffic and environment related factors. We classify and discuss EV energy consumption models in terms of modeling scale (microscopic vs. macroscopic) and methodology (data-driven vs. rule-based). Our review shows trends of increasing macroscopic models that can be used to estimate trip-level EV energy consumption and increasing data-driven models that utilized machine learning technologies to estimate EV energy consumption based on large volume real-world data. We identify research gaps for EV energy consumption models, including the development of energy estimation models for modes other than personal vehicles (e.g., electric buses, electric trucks, and electric non-road vehicles); the development of energy estimation models that are suitable for applications related to vehicle-to-grid integration; and the development of multi-scale energy estimation models as a holistic modeling approach.

Key Words: Electric vehicles, energy consumption estimation, machine learning model

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1. Introduction

The transportation sector is a major energy consumer and contributor to air pollution. Governments around the world are taking steps to address the energy and air pollution problems caused by transportation. A portfolio of strategies should be employed to mitigate transportation-related air pollution and reduce transportation's dependence on fossil fuels [1]. Transportation electrification is among the approaches promoted by industry, public agencies and research communities. Electric vehicles (EVs) are considered as one option to reach low-carbon transportation systems. Countries around the globe are setting aggressive targets to promote EVs or even proposing to ban the future sale of internal combustion engine vehicles [2]. Norway, for example, wants EVs to account for 100 percent of its new-car sales by 2025. China aims to reach 7 million electric vehicle annual sales by the year 2025, which is equivalent to one fifth of its domestic market demand. France, United Kingdom and California in the United States have proclaimed that they will end sales of internal combustion engine vehicles by 2040. The automotive industry expects EVs to become the major powertrain in vehicle market BY 2030 [3].

Despite the environmental benefits and rapid growth of EVs in the global market, the "range anxiety" (i.e., the user's concern about insufficient all electric range of an EV to reach the destination or a charging point) is considered to be one of the major barriers that limit their wide adoption [4]. Reliable and accurate estimation of EV energy consumption can significantly mitigate the range anxiety in that EV users can arrange their itineraries accordingly [5]. Additionally, vehicle-to-grid (V2G) integration has drawn a tremendous amount of attention from research and industry communities in recent years, where EVs can communicate with the power grid to provide short-term demand response services that can balance loads (e.g., peak shaving) within the grid [6]. In this case, the EV energy consumption model can play an important role because it allows optimal management of EV battery charging and discharging activities with the consideration of integrated system efficiency in terms of energy use and transportation needs.

However, estimating the electricity consumption of an EV is a challenging problem. There are various factors influencing electricity consumption. In addition, the model setup can significantly vary depending on the granularity (in both time and space) of estimation. Over the years, a considerable amount of research has been conducted to gather insights into the energy consumption estimation modeling of EVs. The majority of models can be classified from two perspectives: *modeling scale* and *modeling methodology*. The modeling scale refers to the spatial-temporal resolution of energy estimation results, which can be as detailed as energy consumption rate (e.g., kWh per second), or averaged at the individual road link or trip level (e.g., kWh per mile). In literature, modeling scale is determined based on both the purpose of study and data availability. Methodologies of existing models can be roughly classified into *rule-based* and *data-driven*. Rule-based models adopt a "white-box" approach that follows some fundamental physics laws and mimics the dynamics and interactions of various vehicle/powertrain components to estimate energy consumption. Data-driven models draw on a "black-box" approach so that users do not need to understand the physical process of electricity generation and consumption, or even the principles governing vehicle dynamics and powertrain operation, but rely on the exploration of statistical relationship between inputs and energy outputs with certain assumptions or statistical technique.

This study aims to provide a broad perspective of EV electricity consumption estimation and to support the improvement of models and the development of emerging EV applications. The remainder of the paper is organized as follows. Section 2 provides background information on mechanics and components of EV. Section 3 conducts a taxonomy analysis on influential variables for EV energy estimation. Section 4 and Section 5 classify and discuss EV electricity consumption existing models in the literature based on their modeling scale and modeling methodology. Section 6 and 7 summarize possible applications of EV electricity consumption models and conclude the paper.

2. Background

2.1 EV Types and Configuration

In a broad definition, electric vehicles (EVs) refer to road vehicles whose propulsion involves electricity [7], including battery electric vehicles (BEVs); hybrid electric vehicles (HEVs); plug-in hybrid electric vehicles (PHEVs); and fuel-cell electric vehicle (FCEVs). Figure 1 illustrates a general EV configuration which is composed of three major subsystems: a) electric propulsion; b) energy source; and c) auxiliary. As shown in the figure, the electric propulsion subsystem consists of motor(s), transmission, power converter, and electronic control units (ECUs). The energy storage unit, energy management unit, and energy refueling unit comprise the energy source subsystem. In practice, the most widely adopted energy storage device for EVs is battery, due to their characteristics in terms of high energy density, compact size, and reliability [8]. Other devices may include ultra-capacitor (UC), flywheel, and hydrogen tank which can be utilized as an auxiliary energy source or hybrid energy source [9,10]. The auxiliary subsystem involves auxiliary power supply unit, power steering unit, and A/C control unit.

In this study, we focus on BEVs which solely rely on the energy stored in the battery packs to provide power to the drivetrains. Therefore, their range depends directly on the battery capacity, and other factors, including vehicle characteristics (e.g., configuration, weight), driving style, roadway conditions, and weather. Up to date, there are a number of BEV configurations that may vary in: 1) the number of motors used (i.e., single motor, dual motors, and four motors); 2) the motor-transmission connection, such as multi-gear transmission with clutch, fixed gearing with or without differential, and in-wheel motors; and 3) the position of tractive power provision, i.e., front-wheel drive, rear-wheel drive, and all-wheel drive. The selection of different configurations mainly depends on the consideration of size, compactness, weight, cost, reliability and performance (e.g., maximum cruising speed, gradeability, and acceleration) [11].

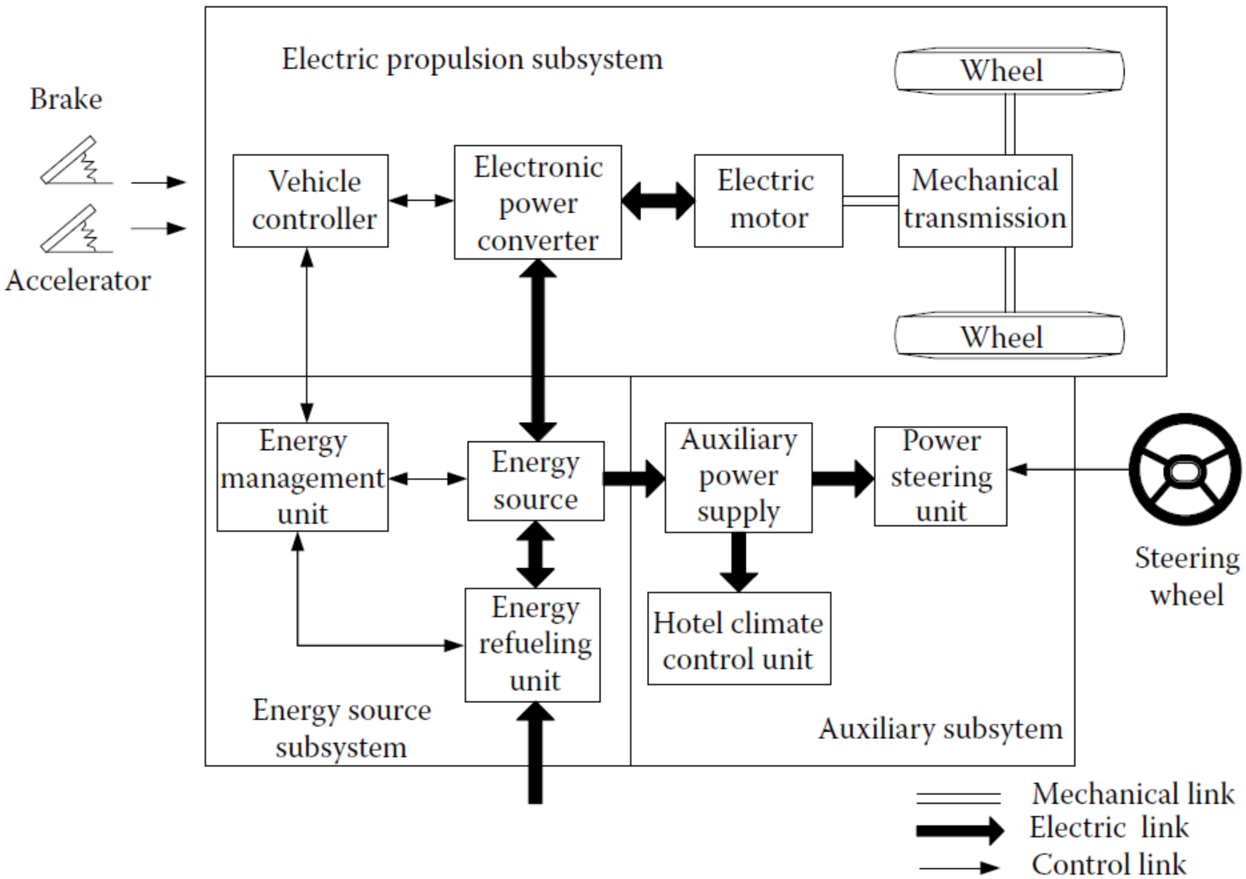

Figure 1. A representative configuration of EV [11].

2.2 BEV Energy Consumption and Regenerative Braking

Due to limited charging facilities and battery capacities, as well as long charging time, estimating BEV's energy consumption is critical for not only environmental sustainability but also market adoption. For BEVs, energy consumption is an integration of the power output measured at the battery terminals (unit in kWh), where the battery charging and discharging modes should be handled separately [12].

During the propulsion mode, the batter power output P_{out} (W) can be estimated by dividing the tractive power at wheels P_{wheel} (W) by the powertrain's efficiency which may consider the power losses in motor drive and transmission. The tractive power at wheels is the product of the vehicle speed v (m/s) and tractive force at wheels F_{wheel} (N) which can be approximated as the sum of the rolling resistance F_{rr} (N), the aerodynamic force F_{ad} (N), the road gradient force F_{rg} (N), and the acceleration force F_{accel} (N). More specifically,

$$P_{out} = \frac{P_{wheel}}{\eta_m \eta_t} = \frac{v \cdot F_{wheel}}{\eta_m \eta_t} = \frac{v \cdot \left(F_{rr} + F_{ad} + F_{rg} + F_{accel}\right)}{\eta_m \eta_t}$$
$$= \frac{v}{\eta_m \eta_t}\left(C_r mg \cos\cos\alpha\ + \frac{\rho_a}{2} C_d A_f v^2 + mg \sin\sin\alpha\ + m\delta \frac{dv}{dt}\right) \tag{1}$$

where η_m and η_t represent the efficiencies of electric motor(s) and transmission, respectively; C_r and C_d are the coefficients associated with rolling resistance and aerodynamic drag, respectively; m (kg) is the vehicle mass; g (9.81 m/s^2) is the standard gravitational acceleration; α (rad) stands for the road gradient; ρ_a (1.2 kg/m^3) refers to the air density; A_f (m^2) is the vehicle's effective cross-sectional area; and δ (constant) is the vehicle rotational inertial factor. Note that the non-traction load (e.g., A/C or lighting load) is not considered in the equation above and wheel slip is ignored.

The battery charging mode for BEVs usually occurs during coasting and braking when the vehicle's kinetic energy – wasted in conventional vehicles – can be partially utilized to generate electricity back to the supply side, which is known as regenerative braking. In other words, part of the braking energy can be recovered by operating the motor as a generator and transferred into the battery. During the regenerative braking mode, the power at the battery terminals can be estimated as

$$P_{in} = \frac{kv}{\eta_m \eta_t}\left(C_r mg\, cos\, cos\, \alpha\ + \frac{\rho_a}{2} C_d A_f v^2 + mg\, sin\, sin\, \alpha\ + m\delta \frac{dv}{dt}\right) \tag{2}$$

where k ($0 < k < 1$) is the regenerative braking factor, indicating the percentage of the overall braking energy that can be recovered by the electric motor(s). In BEVs, the regenerative braking system has to couple with the friction brake, because the regenerative braking itself is not capable of generating enough power to fully stop the vehicle and the addition of friction brake can serve for safety purpose. Therefore, the total energy consumption from the battery E_{batt} related to the motion of BEVs is

$$E_{batt} = \int_t^T P_{batt}\, dt \tag{3}$$

where

$$P_{batt} = \{P_{out}, \qquad in\ traction\ P_{in}, \qquad in\ braking$$

3. Taxonomy of Influential Variables on EV Energy Estimation

3.1 Types of Variables

The energy consumption of an electric vehicle is influenced by a wide range of variables, which can be classified into four categories: 1) vehicle component related; 2) vehicle dynamics related; 3) traffic related; and 4) environment related. These variables are used in both the disaggregated (i.e., original or instantaneously measured) and the statistically or spatio-temporally aggregated formats.

3.1.1 Vehicle Component Related Variables

Vehicle component related parameters govern the operating states of key parts for propulsion (e.g., electric motors, mechanical transmissions), and energy flows within the energy storage and auxiliary subsystems (Figure 1). For example, motor and transmission efficiencies determine the portion of generated energy from the source that can be used for propulsion [13-16, 84, 85, 95, 100, 105]. They vary based on specific configurations of EVs as well as technology of motor and transmission. The battery state of charge (SOC) is found to have impact on energy consumption rate of EVs [13, 19-22]. Studies have shown that the battery SOC can influence instantaneous battery charging/discharging mechanism and efficiency, thus also considered as a critical explanatory variable [13, 22]. Other studies found that the initial battery SOC can aggravate or mitigate the range anxiety of EV drivers and subsequently adjust their driving behaviors which can affect energy consumption [19-21]. Quality of battery, i.e. degradation, is used to estimate changes in trip level energy consumption rate for EV with different age [103]. The auxiliary power that supports the operation of air conditioning, radio, monitor panel, and lights, is non-trivial under certain environmental conditions. Studies have assumed auxiliary load to be either at constant load or estimated using environmental conditions based on real-time measured auxiliary load data [14,17,20,23]. They are studies directly build statistical relationship between vehicle specifications (e.g. engine size, engine technologies, transmission type and efficiency) and energy consumption [83]. Coefficients of rolling resistance, aerodynamic are included in models that estimate EV energy at each second of driving according to physics of law as shown in Equation (1) [86, 91-94, 104-106].

3.1.2 Vehicle Dynamics Related Variables

Vehicle dynamics cover factors that reflect the motion (including speed, acceleration, and tractive/brake torque) of a vehicle or a flow of vehicles. The laws of physics govern direct relationship between these factors and (kinetic) energy demanded by vehicles. Therefore, these variables are commonly used in EV energy estimation models. In existing literature, vehicle dynamics data are seen at instantaneous level (e.g. every one second) or at certain aggregated levels (e.g. trip, road link, 5 minutes, etc.). Speed serves as a key parameter to estimate the road loads that are physically related to rolling resistance, aerodynamic drag, road gradient as depicted in Eq. (1) [13-16,18]. Instantaneous speed and its higher orders (up to the third order) show a strong correlation with the instantaneous EV energy consumption [22, 24-27, 84, 85, 93-95, 100, 104-106]. When energy consumption is estimated at the trip level, average speed [19, 28, 29, 101] and its higher order [30-34] are considered. Other statistics related to speed and acceleration have also been used by researchers for EV energy consumption estimation. For example, studies [35, 36] claimed the highest instantaneous speed and acceleration as surrogate driving behavior modes of drivers and used those features to estimate trip-level energy consumption of EVs. Distribution of speed during a trip is considered as a metric to represent driving behavior of drivers as a way to estimate energy consumption of EV [87]. Profile of speed trajectory is used to estimate possible regenerative braking potential of EVs [88]. Kinetic energy and its change are also highly related to the energy consumed by EVs in motion. Qi et al. [37] used cumulative positive/negative changes in kinetic energy rate (PKE/NKE, as described below) along a trip as influential variables to estimate EV energy consumption and achieved reasonable estimation performance.

$$PKE = \frac{\sum_{i=1}^{N-1} \quad max\,(v_{i+1}^2 - v_i^2, 0)}{\sum_{i=1}^{N-1} \quad (d_{i+1} - d_i)} \tag{4}$$

and

$$NKE = \frac{\sum_{i=1}^{N-1} \quad min\,(v_{i+1}^2 - v_i^2, 0)}{\sum_{i=1}^{N-1} \quad (d_{i+1} - d_i)} \tag{5}$$

where d_i is the cumulative travel distance up to the i-th time step. Vehicle specific power (VSP) is another conventionally defined term to represent the instantaneous vehicle tractive power normalized by the mass. Studies either try to establish relationships between instantaneous VSP and energy consumption or distribution of VSP over a short driving period, also referred as snippets, and average energy consumption rate in that period [33,38].

3.1.3 Traffic Conditions Related Variables

Traffic conditions, such as downstream traffic signal status, congestion levels, and vehicle type mix in traffic flow, can influence EV energy consumption. Particularly, they are used to estimate or validate vehicle dynamics along the downstream segment or rest of the travel route, thus improving its overall energy consumption estimation. Traffic conditions related factors can be classified as categorical and interval variables. Categorical variables determine whether a trip is conducted in certain time or spatial resolution, e.g. time of day (i.e., peak hours vs. non-peak hours), day of week (such as weekdays, weekends, or holidays), or month of year (e.g., seasonal effect). Fetene et al. [19] built a multiple linear regression model which includes “rush hour” as a dummy variable to identify whether a trip happened during peak periods (in the morning or afternoon or not. Masikos et al. [20] proposed a general regression neural network [39] model and used categorical variables to represent trip time within the day of week, month of year and hour of day and the model results show statistical significance of those variables in estimating EV energy consumption. Interval variables represent traffic conditions as a function of continuous vehicle dynamics or overall traffic states. The ratio of idle time or number of stops over travel time can be used as an indicator of en-route traffic condition (more congested if the ratio is higher) along a trip. Studies [28, 35, 40, 102] used this variable and found it to be statistically significant in EV energy model. Efforts are witnessed to create indices of congestion that can be used to estimate energy consumption of EVs. Other studies [28, 89, 99] defined a congestion index (i.e., the mean vehicle speed divided by the standard deviation of speed) and found its significance in the model.

3.1.4 Environment Related Variables

Environment related factors represent information about roadway characteristics or meteorological conditions. These variables influence the energy consumption by introducing disturbance to the road loads or auxiliary loads (e.g., A/C power) for EVs. Widely used variables include road grade [84, 85], road type [19, 22, 41], wind direction, wind speed [23, 19, 41], ambient temperature / humidity [20, 21] and lighting condition [42]. For example, changes in road elevation (i.e., road grade) affect tractive forces needed to overcome road gradient resistance. With advancement in outdoor positioning technology, road grade information becomes available in real-world data collection process and a plethora of literature used it in EV energy estimation models at either the second-by-second level [15, 16, 17] or trip level [20, 23, 27, 28, 31, 32, 34, 40, 41, 43, 44, 84, 85, 92, 100, 101,106]. Another commonly used roadway characteristics related variable in the existing studies is road type, i.e., freeway vs. arterial [19, 22, 41, 90]. Infrastructure attributes of roads, such as traffic light, speed limit, are used as continuous independent variables to estimate energy consumption of EV travelling on the roads [98]. Temperature and humidity are meteorological variables that may affect auxiliary power for heating or cooling demand, as well as operational performance of battery packs in EVs. Because meteorological conditions change gradually over a relatively long time span, related variables are usually included in trip-level energy consumption estimation models [19, 20, 23, 27-29, 31, 41, 45, 96, 97], with the focus of their impacts on auxiliary power demand. Sun et al. tried to explore the relationship between meteorological parameters and battery performance by measuring temperature at battery cells, but they did not include these variables in their proposed model [21]. In a regression model developed by Liu et al. [42], a dummy variable was adopted to represent day or night time and it was found the lighting condition has a strong correlation with EV energy consumption. Ambient temperature and humidity are either measured or estimated based on longitude and latitude of driving location to estimate potential energy consumption for in-cabin cooling and heating [96, 97, 107].

3.2 Aggregation and Disaggregation of Variables

Influential variables for EV energy estimation models can be also classified into two categories, i.e., disaggregated data and aggregated data.

Disaggregated variables refer to data that have the same time or spatial interval as in the collection experiment. The frequency of data collection varies depending on the nature of studies. Data collected at 1 second or finer interval are commonly seen in studies that collect data using on-board diagnostics (OBD) equipment. Common disaggregated input data include 1Hz vehicle speed and acceleration [22, 24, 25, 27, 30], 1Hz vehicle specific power [26, 54], 1Hz kinetic energy [37], 1Hz road grade [15, 16], 1Hz battery state of charge [13, 22] or certain statistics (e.g. maximum or minimum speed) of the above data [19]. Other variables are usually collected at a large time interval because their values do not change frequently, which include Rush house index (whether the travel time is in rush hour) [19,42], congestion index or ratio of idling/stops of a trip or a link travel [28], road type [19,22], meteorology conditions of wind, humidity, temperature [20, 21, 23, 27-29, 31], infrastructure attributes (such as whether a road has traffic light) [41], vehicle attributes (such as weight) [20].

Table 1. Summary of Literature on EV Energy Prediction for Microscale models (red text) and Macroscale models (blue text)

Year	Veh. Type	Methodology		Predicting Variable				Data Source	Ref.
		Data-driven	Rule-based	Dynamics	Traffic	Environment	Component		
2011	PC*	X		X		X	X	**Simulation**	**[85]**
2011	PC	X		X				**Simulation**	**[88]**
2011	PC		X	X			X	**Simulation**	**[93]**
2012	PC	X		X				**Real-world**	**[87]**
2012	PC	X		X		X	X	**Real-world**	**[101]**
2012	PC		X	X			X	**Simulation**	**[104]**
2013	PC	X		X		X		**Real-world**	**[90]**
2013	PC		X	X			X	**Simulation**	**[91]**
2013	PC	X			X			**Simulation**	**[99]**
2014	PC	X		X			X	**Simulation**	**[86]**
2014	PC	X		X				**Real-world**	**[26]**
2014	PC	X		X				**Real-world**	**[43]**
2014	PC		X	X			X	**Simulation**	**[46]**
2014	PC		X	X			X	**Simulation**	**[94]**
2014	PC	X		X	X	X	X	**Real-world**	**[108]**
2015	PC		X	X		X	X	**Real-world**	**[92]**
2015	PC		X	X			X	**Simulation**	**[14]**
2015	PC		X	X			X	**Real-world**	**[16]**
2015	PC	X		X	X	X	X	**Real-world**	**[20]**
2015	PC	X		X				**Real-world**	**[22]**
2015	PC	X		X				**Real-world**	**[25]**
2015	PC	X		X	X		X	**Real-world**	**[40]**
2015	PC		X	X		X	X	**Simulation**	**[84]**
2015	PC	X			X	X		**Real-world**	**[89]**
2015	PC		X	X			X	**Simulation**	**[95]**
2015	PC	X				X		**Real-world**	**[96]**
2015	PC	X				X		**Real-world**	**[98]**
2015	PC		X	X			X	**Real-world**	**[101]**
2016	PC		X	X			X	**Simulation**	**[13]**
2016	PC		X	X		X	X	**Real-world**	**[15]**
2016	PC	X		X	X	X	X	**Real-world**	**[28]**
2016	PC	X		X	X	X	X	**Real-world**	**[42]**
2016	PC		X	X			X	**Real-world**	**[48]**
2016	PC	X		X				**Real-world**	**[54]**
2016	PC	X		X				**Real-world**	**[56]**

2016	PC		X	X			X	Simulation	[105]
2017	PC			X	X	X	X	Real-world	[19]
2017	PC	X		X		X	X	Real-world	[24]
2017	PC	X		X			X	Real-world	[27]
2017	PC	X		X			X	Real-world	[30]
2017	PC	X		X		X	X	Simulation	[34]
2017	PC	X		X		X		Real-world	[44]
2017	PC	X		X		X		Real-world	[45]
2017	PC	X		X				Real-world	[53]
2017	PC	X		X			X	Real-world	[55]
2017	Train		X	X			X	Real-world	[60]
2017	PC	X		X		X		Real-world	[107]
2018	PC	X		X		X		Real-world	[17]
2018	PC	X		X			X	Real-world	[29]
2018	PC	X		X		X	X	Real-world	[31]
2018	PC	X		X	X			Real-world	[35]
2018	Bus	X		X				Real-world	[36]
2018	PC	X		X		X		Real-world	[37]
2018	PC		X	X			X	Real-world	[41]
2018	PC	X		X				Simulation	[47]
2018	PC		X	X			X	Simulation	[50]
2018	PC	X		X		X		Real-world	[57]
2018	Truck		X	X		X	X	Real-world	[106]
2019	Non-Road	X		X	X			Real-world	[18]
2019	PC	X		X			X	Real-world	[21]
2019	Bus	X		X	X		X	Simulation	[23]
2019	PC		X	X			X	Real-world	[32]
2019	PC	X		X				Real-world	[33]
2019	PC		X	X			X	Simulation	[49]
2019	PC	X		X				Real-world	[51]
2019	PC	X		X		X		Real-world	[52]
2019	PC	X		X			X	Real-world	[58]
2019	Truck		X	X		X	X	Simulation	[59]
2019	PC		X	X		X		Real-world	[61]
2019	Bus		X	X		X	X	Real-world	[62]
2019	PC		X	X			X	Simulation	[63]
2019	PC		X	X			X	Real-world	[64]
2019	PC	X		X		X	X	Simulation	[65]
2019	PC	X		X		X	X	Simulation	[66]
2019	PC	X		X			X	Real-world	[67]
2019	PC	X				X		Real-world	[97]
2019	PC	X					X	Simulation	[83]

2019	PC	X		X		X	X	**Real-world**	**[100]**
2019	PC	X		X	X		X	**Real-world**	**[102]**
2019	PC	X					X	**Real-world**	**[103]**
2019	PC	X		X	X	X		**Simulation**	**[109]**

*PC – Passenger Car

Aggregated variables refer to data that are aggregated after initially collected and presented at a different time interval. With OBD or GPS technologies, speed and acceleration data are easily obtained at 1Hz level and then averaged to different minute or hour levels [21, 23, 28, 29, 31, 34-36, 40, 41, 43]. In addition, state and local transportation authorities routinely collect and publish traffic flow and volume information of roads in their jurisdictions which are usually aggregated at every 5 minutes, 15 minutes, 30 minutes or 1 hour.

4. Modeling Scale

EV Energy estimation models can be classified based on their modeling scale, which further determine areas of application.

Microscopic-scale models can estimate energy consumption of EV at high frequency, typically 1Hz. Thus, they have been widely used in applications related to microscopic vehicle dynamics, and optimal control of EV strings or traffic operation involved with EVs. A representative example is EV eco-driving which uses microscopic models to optimize real-time vehicle control, particularly in congestion mitigation on corridor or signalized intersection [24, 47, 56, 109]. EV routing studies used microscopic energy estimation models to dynamically determine energy efficient routes [13, 59, 108]. Microscale models were developed for evaluating energy implications of EV in traffic simulation [15, 26, 30, 32].

Macroscopic models can explore the relationship between energy consumption and characteristics of driving at an aggregated spatial and/or temporal span. Thus, they are used in applications that require energy information of EVs in similar spatial and temporal space, such as EV fleet management, region-wide planning of charging infrastructure or EV adoption, large-scale EV related energy portfolio prediction, and etc. One study tried to create a map showing EV energy consumption on each road link based on link-specific traffic pattern (e.g. average speed), geometry attributes (e.g. number of lanes, link width) [20]. Other studies looked at evaluating capability of EV driving range in sustaining future trips [19, 21, 50, 52, 58].

Figure 2 summarizes the existing relevant studies. As can be seen from the figure, the number of references on energy consumption of electric vehicles has been increasing since 2011, keeping flat between 2015 and 2018, and then rocketing in 2019. By further differentiating the references by the source of data (i.e., real-world vs. simulation), we observe that EV energy estimation models based on the real-world data dominate the literature and the share of macroscale models keeps increasing, which implies a promising trend of macroscopic applications in transportation planning and operations for EVs. When differentiating the references by the vehicle type, we observe that the majority of the existing studies have focused on passenger cars while a significant knowledge gap is present for other vehicle categories, such as transit vehicles, heavy-duty trucks, trains or locomotives, and non-road vehicles (e.g., construction, agriculture equipment). They start to appear in the literature only after 2017, which may be due to their slower electrification process compared to passenger cars.

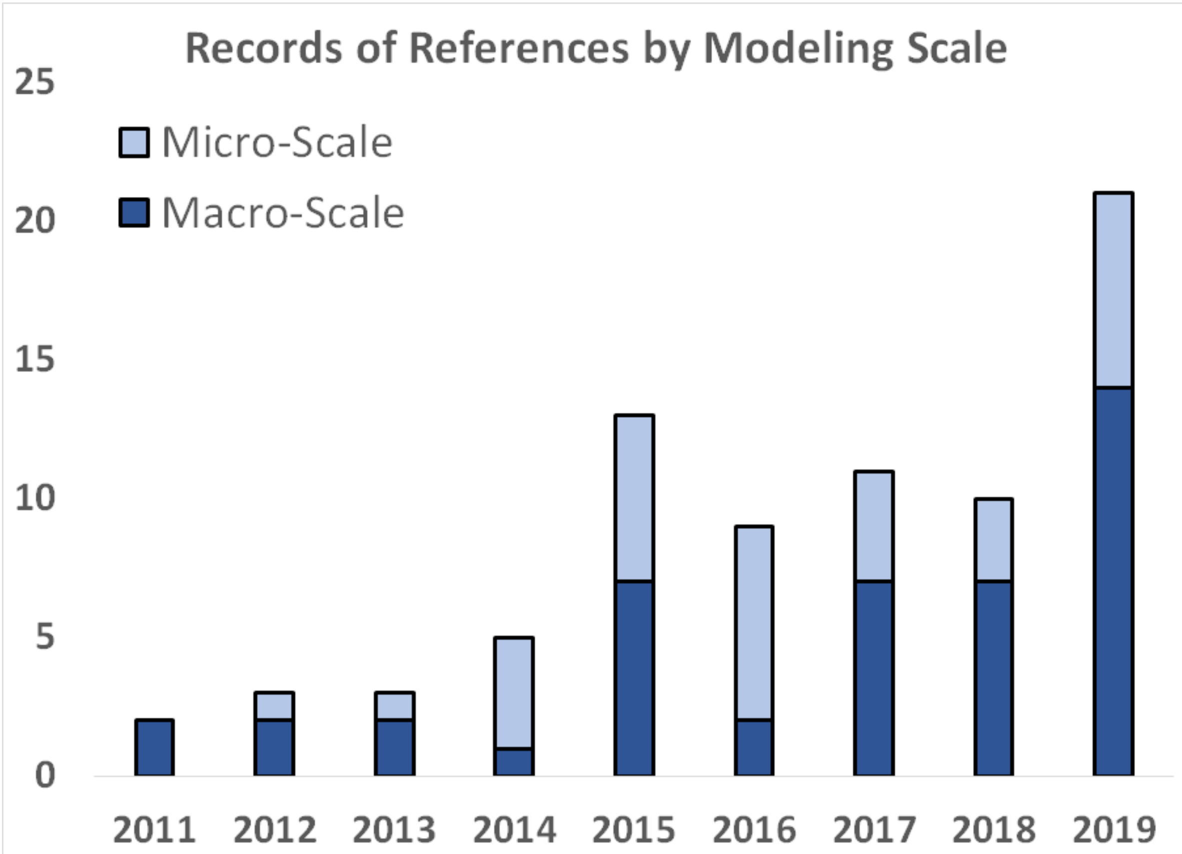

Fig. 2: Number of research papers for microscale and macroscale electric vehicle energy consumption estimation model for each calendar year.

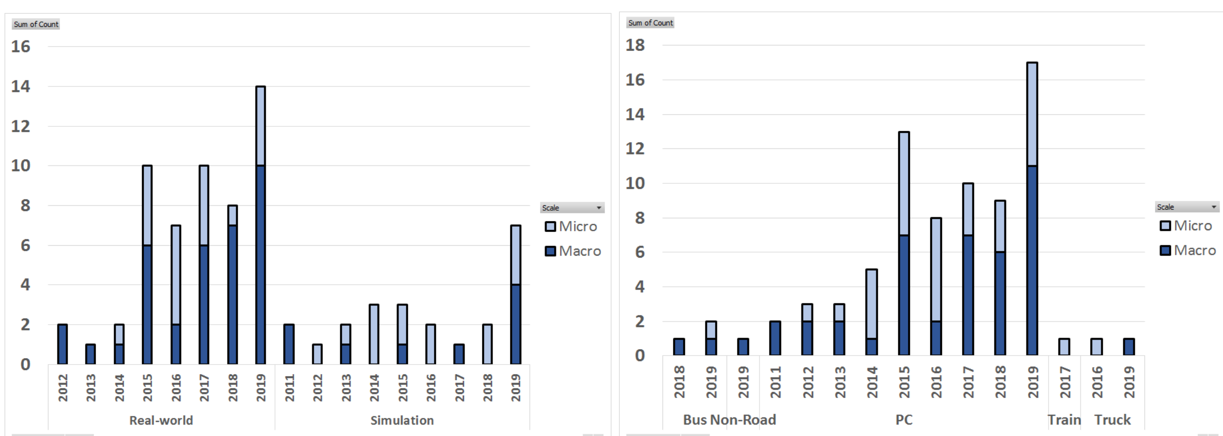

Fig. 3: Number of research papers for microscale and macroscale electric vehicle energy consumption estimation model by data source (Fig. 2a, left) and by vehicle type (Fig. 2b, right) for each calendar year.

5. Modeling Methodology

According to our review on the majority of literature, existing EV energy modeling methods can be classified into three categories: a) rule-based; b) data-driven; and c) hybrid, as shown in Figure 4.

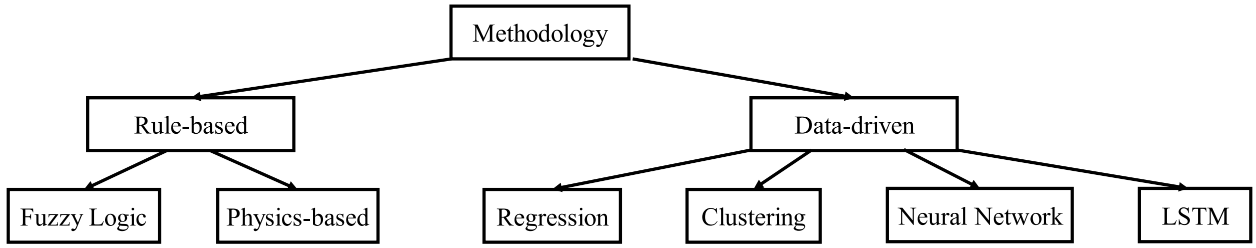

Fig. 4: The classification scheme for the state-of-the-art EV energy modeling methods.

5.1 Rule-based

The configuration and dynamics of battery EVs are well defined on Section 2. Compared to an internal combination engine powered vehicle, the configuration and energy flow of an EV is less complicated. In addition, the component-wise energy efficiency of an EV is less varied. Therefore, many studies estimated the EV energy consumption rate (i.e., in the microscale) by following the Newton's Law to calculate the tractive power at wheel and assuming constant powertrain efficiency [68-72]. Others developed EV energy estimation models based on car-following models and downstream traffic information [73]. To model the regenerative braking effects, some researchers applied the fuzzy logic [74], while others assumed simple relationship (e.g., as a piecewise linear function) with the vehicle's speed [75]. Although the rule-based models are relatively simple, their modeling accuracy when applying to specific vehicle or scenario may not be satisfactory. In addition, there are a few challenges to extend the application of these models to a macroscopic scale: 1) estimation errors may be accumulated if the energy consumption by a fleet of EVs is concerned; and 2) energy impacts due to the interaction among different players are difficult to model in a complicated system (e.g., a region-wide transportation scenario).

5.2 Data-driven

Thanks to improvements in sensors, automotive electronics and telematics in recent years, more and more data (in terms of both type and amount) became available for EV energy consumption modeling where a variety of data-driven techniques have been applied. To date, the most widely used statistical method is the multi-variate linear regression (MLR) [76-80]. The MLR-based EV energy consumption models usually include instantaneous speed of different orders, acceleration of different orders, and their interaction terms, as the independent variables and assume their relationship with a linear predictor function. Due to rapid advancements in advanced machine learning techniques and high-performance computing, a few representative algorithms such as artificial neural network [43] and long short-term memory [17] have been employed to estimate the EV energy consumption. In addition, other unsupervised learning methods (e.g., clustering, PCA) have been used for data preprocessing or pattern recognition [21, 35, 55, 57].

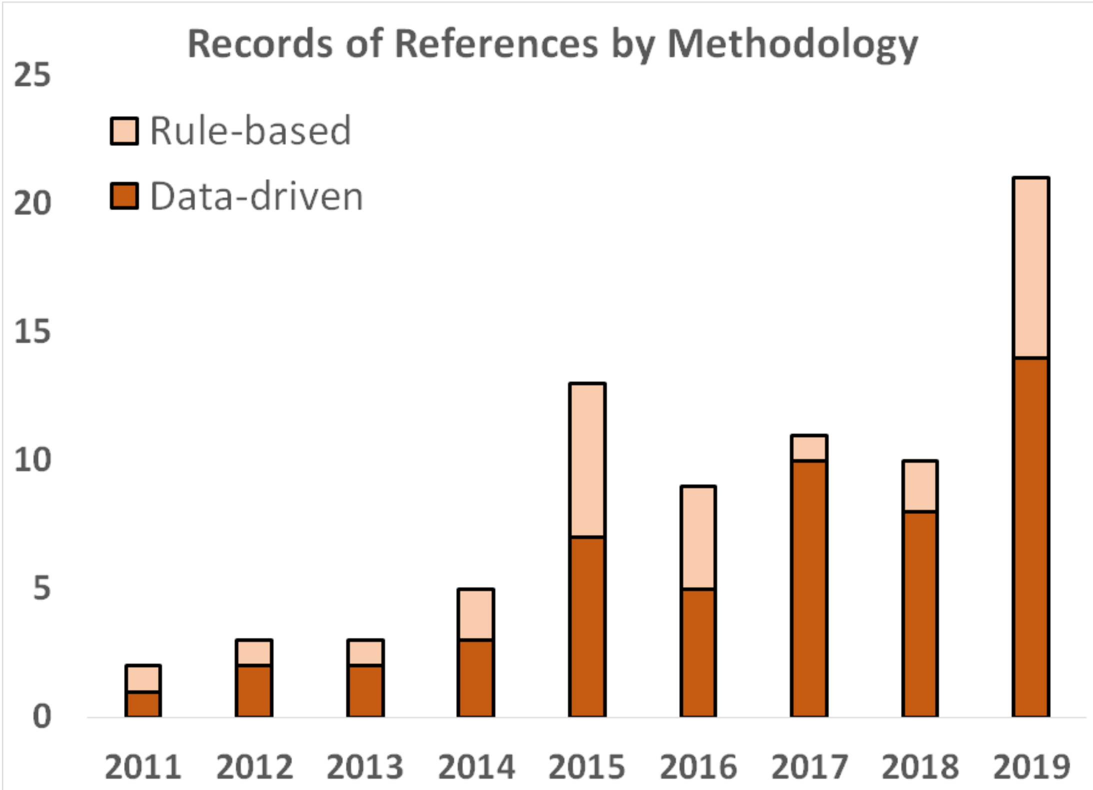

Fig. 5: Number of research papers for electric vehicle energy consumption estimation model for each calendar year.

Figure 5 shows that even though the volume of literature related to electric vehicle energy consumption has been increasing over the past few years, the number of data-driven models started to increase only after 2015. However, data-driven models became the dominant methodology in recent years. A further glimpse at the records by data source and vehicle type reveals that a majority of studies have been focused on the development of data-driven models and calibration of model coefficients with real-world data. If the vehicle type is differentiated, the data-driven methods have been dominantly used to model the energy consumption of electric passenger cars, buses and non-road vehicle, while rule-based methods are dominant in estimation models for trucks and trains.

Unlike the rule-based methods that are usually targeting microscopic models, data-driven methods can be applied to various data sources, such as powertrain/vehicle dynamics, traffic information, driver's behavior, network profile, and meteorological conditions, with different spatio-temporal aggregation levels (e.g., link-based, every 5 minute). In addition, the developed models are usually customized for specific vehicles, drivers or scenarios whose results may be very dataset dependent and it could be quite challenging to generalize the conclusion.

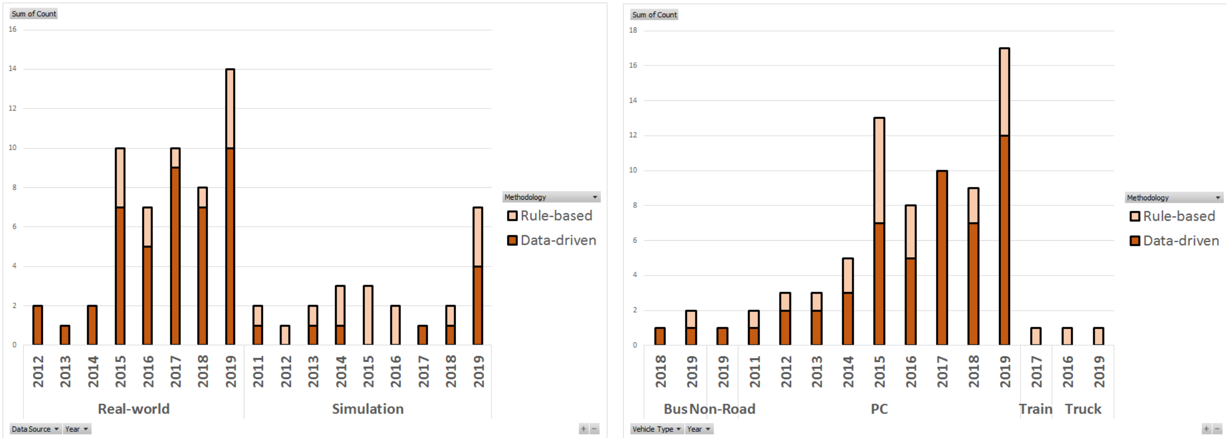

Fig. 6: Number of research papers for electric vehicle energy consumption estimation model using rule-based and data-driven methods by data source (Fig. 2a, left) and by vehicle type (Fig 2b, right) for each calendar year.

Despite all the aforementioned advantages, data-driven EV energy consumption models have two main limitations. Firstly, data-driven estimation models might not perform satisfactorily outside their trained/test datasets. Therefore, it is important to ensure that the datasets used for training are representative of the entire population and contain sufficient varieties of information. Secondly, data-driven estimation models are black-box models which have the potential to provide satisfactory accuracy, but are limited in explaining details of the different parameters and their implications in energy consumption.

To well balance the advantages of both rule-based methods (model simplicity and generalization) and data-driven methods (model accuracy and customization), Ye et al. proposed a hybrid approach to estimating the EV energy consumption rate [24]. In this approach, the feature selection roots in the physical principles instead of specific datasets, while the model coefficients or system parameters are trained from the data to achieve customized performance for specific scenarios.

6. Discussion

It is self-evident that different energy consumption models are suitable for different energy-focused electric vehicle applications. Figure 7 presents some typical scenarios of EV energy model application across different scales. For example, energy consumption rate models are applicable to the development of eco-driving (mainly longitudinal maneuvers) systems for individual EVs or eco-friendly traffic signal control at intersections. Aggregated models may fit well for region-wide EV applications considering a long-term effect.

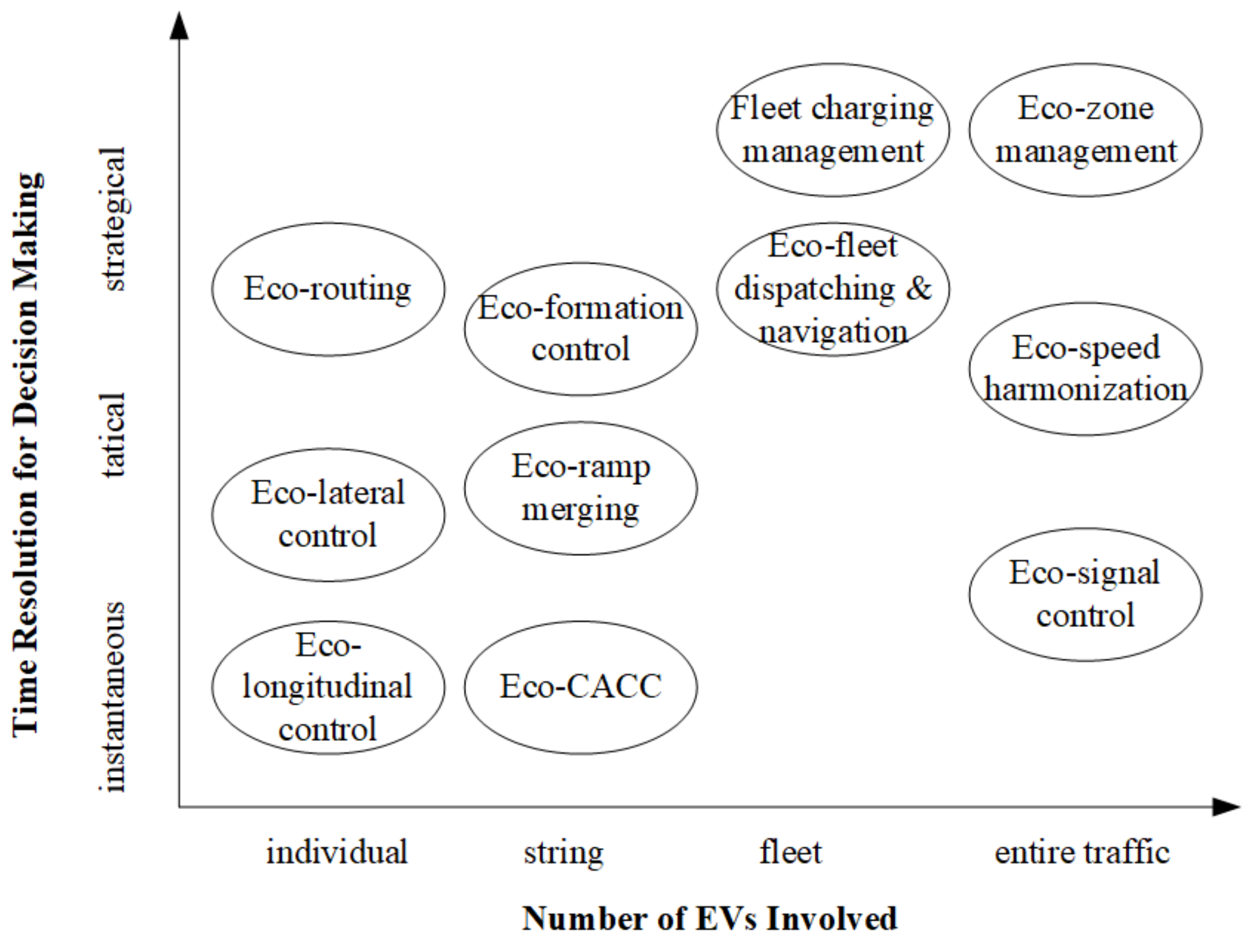

Fig. 7: EV Energy model applications under different time resolution.

The results of this review indicate some research areas that may require more attention:

1) *Energy estimation for vehicles other than passenger cars*: The majority of up-to-date literature on EV energy estimation model has been focused on passenger cars. However, significant progress has been witnessed in the development of freight and transit electrification. Given the fact that trucks consume more than 20% of total transportation energy [81] and public transit is deemed as a viable solution to the transportation in many developing countries or populated areas, more research should be conducted for modeling the energy consumption of electric trucks and buses.
2) *Application for vehicle-to-grid integration*: The vehicle-to-grid technology is considered as an emerging and cost-effective solution to optimizing both EV usage and power grid operation in a cooperative manner. One challenge in vehicle-to-grid integration system is to find a computationally efficient algorithm that can handle real-time EV energy consumption analysis and large-scale charging facility scheduling optimization [82]. Specifically, the embedded EV energy consumption model should be capable of estimating and comparing EV energy consumption over different candidate driving scenarios.
3) *Development of multi-scale EV energy estimation model:* Multi-scale models are able to simultaneously cover important features at different resolutions of time and/or space. Such integrated modeling approach may preserve the information at different levels, from individual component to traffic in a collective manner. All existing studies have been

focused on either microscale or macroscale EV energy estimation. It will be useful to develop multi-scale EV energy estimation models which can provide consistent information for energy estimation across different scales. However, one major challenge would be to develop algorithms or methodologies to find accurate and efficient solutions to multiscale modeling problems.

7. Conclusion

This paper presents an overview of recent research efforts in the area of electric vehicle energy consumption estimation. A set of energy consumption estimation models were reviewed in terms of influential variables (vehicle component, driving dynamics, traffic, environment), modeling scale (microscopic vs. macroscopic), methodology (rule-based vs. data-driven). The properties of the data used for these models were also reviewed, including the source of data (simulation vs. real-world), the type of vehicles to be modeled (car, truck, bus, train, or non-road vehicles) and publication year of literature (2016-2019).

Vehicle component factors determine the operation of key parts for propulsion and energy flow within vehicles. They are naturally used in rule-based models at micro scale because their changes can instantaneously and directly influence energy output at electric motor. But certain aggregated formats of these factors are also witnessed in data-driven macroscale models in recent literature. Vehicle dynamics factors represent motion of vehicles. The instantaneous or aggregated formats of vehicle dynamics are the most widely used for the EV energy modeling, regardless of the modeling scale or methodology. Traffic condition factors can be used to supplement information provided by vehicle dynamics. Traffic at one specific time equals to instantaneous speed in vehicle dynamics. Therefore, microscale models do not consider traffic factors. Macroscale models use traffic factors as proxy to vehicle dynamics in a certain period of time. Environment factors mainly relate to roadway characteristics or meteorological conditions. They are commonly used in macroscale models, especially the road grade which is used in both micro- and macroscale models. According to the summary, data-driven EV energy consumption estimation and its applications have been attracting increasing research attention in the past few years, whereas rule-based models dominate earlier literature. In addition, a growing number of macro scale models in the literature are observed in recent years. Although models with different scales may be developed to serve different purposes and application scenarios, efforts on multi-scale model development would be valuable as an integrated solution to preserving the information consistency from various spatio-temporal resolutions and aggregated levels.

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