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Review Article

A Survey of Energy Consumption Models for Electric Vehicles: From Simulation to Real-World Applications

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Abstract

Electric vehicles (EVs) are essential to low-carbon mobility. For optimal performance, infrastructure development, and energy efficiency, EV adoption requires accurate and reliable energy consumption models. This study discusses the latest EV energy consumption modelling advances, pinpointing four main aspects: vehicle components, dynamics, traffic circumstances, and environmental factors. EV energy consumption models are classified by scale (microscopic vs. macroscopic) and methodology (data-driven vs. rule-based). Microscopic models analyse driving behaviours to estimate short-term energy usage, while macroscopic models estimate trip-level energy consumption for large-scale planning. The paper also notes a shift towards data-driven models, which use machine learning and massive datasets for accuracy. Rule-based models use physical concepts and empirical formulas. Many research gaps remain despite advances. Energy models for electric buses, lorries, and industrial vehicles are needed. Vehicle-to-grid (V2G) integration models need improvement to allow bidirectional energy exchange. Finally, multiscale energy models, which combine microscopic and macroscopic techniques, may improve EV energy estimation accuracy and application. This study highlights emerging trends and future research goals, emphasising scalable, intelligent, and flexible energy consumption models for EV uptake and sustainable mobility.

Keywords: Elecrtic vehicles (EV), EV energy model, macro- scopic models, Vehicle-to-grid (V2G),sustainable mobility

1 Introduction

Transportation uses a lot of energy and pollutes the air. Transportation's environmental and energy impacts are being addressed by governments worldwide. To reduce air pollution and fossil fuel use in this sector, multiple solutions are needed [1] [2]. Transportation electrification is gaining popularity among businesses, governments, and researchers. Electric vehicles (EVs) are essential for low-carbon mobility. Many nations are setting aggressive objectives to hasten EV adoption, with some seeking to phase out internal combustion engine vehicles [3]. Norway intends for 100% of new car sales to be EVs by 2025. China plans to sell 7 million EVs yearly by 2025, 20% of its domestic market. France, the UK, and California intend to stop selling ICE cars by 2040. The automobile industry predicts that EVs will be the main power plant by 2030 [4]. Despite EVs' environmental benefits and increasing global growth, "range anxiety"—the worry that an EV's battery range may not be enough to reach a destination or charging station—remains a major barrier to adoption [5]. Users can better plan their trips by accurately and reliably forecasting EV energy consumption [5]. Vehicle-to-grid (V2G) integration has also garnered attention from researchers and industry specialists. EVs can connect with the power grid via V2G technology to provide short-term demand response services like load balancing and peak shaving [6] [7]. An EV energy consumption model optimizes battery charging and discharging, assuring system-wide energy efficiency and satisfying transportation demands. Estimating electric vehicle (EV) energy consumption is complicated by many factors. Based on estimation, geographic and temporal resolution, model structure, and setup might vary greatly. EV energy consumption estimating models have been studied extensively over the years. Model scale and approach are the key categories of these models. The modeling scale describes energy estimation results' geographical and temporal detail. Energy consumption rates can range from kilowatt-hours per second to energy usage per mile or journey. Study scale varies on research goals and data availability. Rule-based and data-driven modeling methods are common. Rule-based models evaluate energy consumption using "white-box" physical principles and vehicle component and powertrain dynamics simulations. Data-driven models are "black boxes" since they don't require physical process expertise. These models use assumptions or statistical approaches to analyze input-energy output relationships.

The rest of the paper is organized as follows. Section 2 provides the background necessary to understand the domain of electric vehicle (EV) energy estimation. Section 3 introduces a taxonomy of key factors impacting EV energy estimation, categorizing them into vehicle-specific, environmental, and behavioral dimensions. Section 4 discusses the modeling scale. Section 5 focuses on the modeling methodology, outlining physics-based, data-driven, and hybrid approaches, and evaluating their applicability across various scenarios. Section 6 presents a critical discussion of the findings, research gaps, and potential future directions. Finally, Section 7 concludes the paper.

2 Background

2.1 Electric Vehicle Categories and Design Specifications

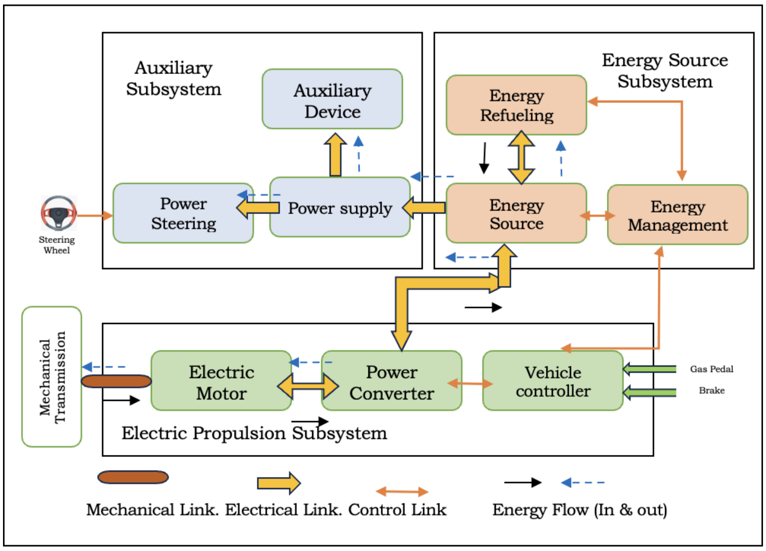

Figure 2.1: The onfiguration of EV

Electric vehicles (EVs) [8] [9] are described as road vehicles that employ electricity for propulsion [10] [11]. This category encompasses battery electric cars (BEVs) [12], hybrid electric vehicles (HEVs) [13], plug-in hybrid electric vehicles (PHEVs) [14], and fuel-cell electric vehicles (FCEVs) [15]. A standard electric vehicle configuration, seen in Figure 2.1, [16] consists of three primary subsystems: the electric propulsion system, the energy supply system, and the auxiliary system [17]. The electric propulsion subsystem comprises essential components like motors, a gearbox system, a power converter, and electronic control units. The energy source subsystem comprises an energy storage unit, an energy management unit, and an energy refuelling unit. Batteries are the predominant energy storage technologies in electric vehicles, attributed to their high energy density, compact design, and reliability. Alternative energy storage solutions, including ultra-capacitors, flywheels, and hydrogen tanks, may function as supplementary or hybrid energy sources [18] [19]. Finally, the auxiliary subsystem includes components such as the auxiliary power supply unit, the power steering unit, and the air conditioning control unit.

This study examines battery electric vehicles (BEVs), which depend exclusively on energy stored in battery packs to operate their drivetrains. Thus, their driving range is directly affected by battery capacity and various other parameters, including vehicle specs (e.g., design, weight), driving habits, road conditions, and weather conditions. Presently, BEV configurations may vary according to several factors: (a) the quantity of motors, encompassing single-motor, dual-motor, or quad-motor arrangements; (b) the linkage between the motor and the transmission, including multi-gear transmissions with clutches, fixed gearing systems with or without differentials, and in-wheel motor architectures; and (c) the drivetrain type, which can be front-wheel drive, rear-wheel drive, or all-wheel drive. Most of the time, the choice of configuration is based on factors like size, weight, dependability, dependability, and performance indicators such as top speed, ability to climb, and acceleration [20].

2.2 BEV Energy Consumption and Regenerative Braking

Considering the limitations of charging infrastructure, battery capacity, and prolonged charging times, precise estimation of energy usage in battery electric vehicles (BEVs) is crucial for environmental sustainability and broader commercial acceptability. In battery electric vehicles (BEVs), energy consumption is dictated by the total power output at the battery terminals (measured in kWh) [21], with specific considerations for the charging and discharging operations.

In propulsion mode, the textbfbattery power output ($P_textout$) in watts (W) can be calculated by dividing the textbftractive power at the wheels ($P_textwheel$) by the textbfpowertrain efficiency ($eta_m eta_t$), which considers power losses in the motor drive and gearbox system.

The tractive power at the wheels is determined by multiplying the vehicle speed (v, in meters per second) by the tractive force at the wheels (F_{wheel}, in newtons).

The tractive force can be estimated as the aggregate of the forces resulting from rolling resistance (F_{rr}), aerodynamic drag (F_{ad}), road gradient (F_{rg}), and acceleration (F_{accel}).

In particular:

$$P_{\text{out}} = \frac{P_{\text{wheel}}}{\eta_m \eta_t} = \frac{v \cdot F_{\text{wheel}}}{\eta_m \cdot \eta_t} = \frac{v \cdot \left(F_{\text{rr}} + F_{\text{ad}} + F_{\text{rg}} + F_{\text{accel}}\right)}{\eta_m \cdot \eta_t} \tag{1}$$

By substituting the equations for these forces, the equation transforms into:

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

Where:

- η_m and η_t denote the efficiencies of the electric motor(s) and the transmission, respectively.
- C_r and C_d are the coefficients for rolling resistance and aerodynamic drag, respectively.
- m (kg) represents the vehicle's mass.
- g (9.81 m/s^2) is the acceleration due to gravity.
- α (rad) indicates the road gradient.
- ρ_a (1.2 kg/m^3) is the air density.
- A_f (m^2) refers to the vehicle's effective frontal area.
- δ (dimensionless) accounts for the vehicle's rotational inertial factor.

It is important to note that this equation does not consider non-traction loads, such as air conditioning or lighting systems, and assumes no wheel slip occurs.

In Battery Electric Vehicles (BEVs), battery charging often takes place during coasting and braking phases. During these intervals, the vehicle's kinetic energy—typically squandered in conventional vehicles—is partially transformed into electrical energy and stored in the battery via a process known as regenerative braking. This entails the motor operating as a generator to recuperate a portion of the braking energy and convey it to the battery.

The power input at the battery terminals during regenerative braking can be articulated as:

$$P_{\text{in}} = \frac{kv}{\eta_m \eta_t} \left(C_r mg \cos \alpha + \frac{\rho_a}{2} C_d A_f v^2 + mg \sin \alpha + m\delta \frac{dv}{dt} \right) \tag{3}$$

In this context, $k(0 < k < 1)$ denotes the regenerative braking factor, indicating the fraction of the total braking energy that can be recuperated by the electric motor(s). In battery electric vehicles, regenerative braking must operate alongside friction brakes, as regenerative braking alone is insufficient to entirely halt the vehicle. The friction brakes additionally function as a safety backup.

The cumulative energy expenditure from the battery, E_{batt}, throughout the operation of a Battery Electric Vehicle (BEV) can be determined as:

$$E_{\text{batt}} = \int_t^T P_{\text{batt}}\, dt \tag{4}$$

where,

$P_{\text{batt}} = P_{\text{out}}$ during traction mode and $P_{\text{batt}} = P_{\text{in}}$ during braking mode

This framework provides a comprehensive approach to understanding energy recovery and consumption in BEVs.

3 Taxonomy of Key Factors Impacting EV Energy Estimation

Many variables affect electric vehicle (EV) energy consumption estimation, which can be categorised. These elements are essential for energy estimating model accuracy and dependability. Vehicle components including battery capacity, motor efficiency, and drivetrain design affect energy usage. Vehicle dynamics—speed, acceleration, and braking—determine energy needs. Congestion, stop-and-go driving, and traffic patterns affect energy use. Finally, environmental factors including road grade, ambient temperature, and wind resistance affect vehicle external load and energy efficiency. This comprehensive taxonomy of significant variables helps construct more robust and accurate energy estimation models by organising the many aspects affecting EV energy usage.

3.1 Classification of Variables

Four main elements affect an electric vehicle's energy consumption: vehicle components, dynamics, traffic, and environment. Disaggregated data includes original or directly measured data, while aggregated data uses statistical or spatiotemporal processing to provide larger insights.

3.1.1 Vehicle Component-Related Variables

Vehicle component-related characteristics affect the operational states of important propulsion components (e.g., electric motors, mechanical transmissions) and energy flows in energy storage and auxiliary subsystems. Motor and gearbox efficiencies affect how much energy the source generates for propulsion, depending on the EV setup and technology. The battery's quick charging and draining mechanisms and efficiency depend on its state of charge (SOC), which affects energy consumption. Thus, SOC is a key explanatory variable since it affects energy usage and range anxiety, which can change driving behaviour.

Another important aspect in EV energy consumption estimates is battery condition, including depreciation over time. Under certain environmental conditions, air conditioning, infotainment, and lighting power demands can also dramatically effect energy use. Some studies estimate auxiliary power loads using real-time data or ambient factors, while others assume continuous loads. Connected and autonomous vehicle sensors (e.g., LiDAR, cameras), edge computing, and wireless communication devices may raise supplementary energy consumption, requiring further research.

Furthermore, statistical models have been developed to correlate vehicle specifications—such as engine size, engine technologies, and gearbox type—with energy usage. As per physics, physical models use rolling resistance and aerodynamic coefficients to predict energy consumption per second. These extensive investigations reveal how car components affect EV energy efficiency and consumption.

3.1.2 Vehicle Dynamics-Related Variables

Vehicle dynamics include speed, acceleration, and tractive or braking torque. Physics governs these parameters, which link motion to vehicle kinetic energy. Thus, EV energy consumption models incorporate vehicle dynamics extensively. Existing studies analyse these characteristics instantaneously (e.g., every second) or over trips, road links, or time intervals like five minutes.

Equation (1) shows that speed is crucial for evaluating road loads, including rolling resistance, aerodynamic drag, and road gradient. Speed and its higher-order derivatives (up to the third order) substantially correspond with instantaneous energy usage. Most trip-level energy consumption estimates employ average speed and its higher orders. Researchers also used speed and acceleration statistics. Studying peak instantaneous speed and acceleration as surrogate measures of driving behaviour can determine trip-level energy expenditure.

Another statistic used to estimate EV energy consumption and driver behaviour is trip speed distribution. However, speed trajectories estimate EV regenerative braking potential. Vehicle motion energy consumption is also linked to positive and negative kinetic energy changes. Qi et al. [22] showed that cumulative variations in kinetic energy rate during a journey affect energy consumption estimation, producing trustworthy models. These findings emphasise the importance of vehicle dynamics in estimating electric car energy demands.

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

and

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

The cumulative travel distance up to the i^{th} step is represented by d_i. Another often used parameter is vehicle-specific power (VSP), which is a vehicle's instantaneous tractive power normalised by mass. Research has examined the association between immediate VSP and energy usage or the distribution of VSP across brief driving durations, or "snippets." To determine EV energy usage trends, these snippets' average energy consumption rate is often examined [33, 38].

3.1.3 Traffic Conditions-Related Variables

Traffic variables including downstream traffic light state, congestion, and vehicle mix affect EV energy use. These parameters are often utilised to predict or validate vehicle dynamics in downstream portions or the rest of a travel route, improving energy consumption estimation. Traffic variables might be categorical or interval.

Classification are used to determine if a journey occurs during specific temporal or spatial conditions, such as peak vs. non-peak hours, weekdays, weekends, or holidays, or the month (to capture seasonal effects). Fetene et al. [23] created a multiple linear regression model with "rush hour" as a dummy variable to signify peak traffic trips. Masikos et al. [24] used a general regression neural network model to estimate EV energy usage using categorical factors as day of the week, month, and hour.

However, interval variables measure traffic conditions continuously by measuring vehicle dynamics or traffic states. Congestion is generally measured by idle time or stops to travel time (with larger ratios indicating more congestion). This variable is statistically significant in EV energy models [25] [26] [27]. Congestion indicators for energy consumption estimation have been developed elsewhere. In energy consumption models, a congestion index (mean vehicle speed divided by standard deviation) was a significant predictor [28] [29] [30]. These methods emphasise the importance of traffic circumstances in EV energy modelling and estimation.

3.1.4 Environment-Related Variables

EV energy consumption is affected by roadway characteristics and meteorological conditions, which affect tractive forces and auxiliary loads (e.g., air conditioning). Road grade, type, wind speed and direction, temperature, humidity, and lighting are studied.

Road grade affects tractive forces needed to overcome gradient resistance. Road grade data is now available in real time thanks to outdoor positioning technologies and is often included in EV energy calculation models, either second-by-second or over trips. Energy usage varies with road type, such as motorways versus arterials, according to traffic flow and speed. Continuous variables in EV energy models include infrastructural factors like traffic lights and speed limits.

Ambient temperature and humidity affect auxiliary power demands, such as for heating and cooling systems, and battery pack performance. Trip-level energy estimation models include these conditions because they vary gradually. The vehicle's longitude and latitude are used to measure or estimate ambient temperature and humidity to determine in-cabin cooling and heating energy consumption. Their regression model included day vs. night lighting settings as a dummy variable and found a high association with energy use.

Sun et al. [31] measured cell temperatures to study climatic elements and battery performance, but these variables are not always included in proposed models. However, EV energy consumption models are more accurate when roadway and environmental parameters are included to account for exterior vehicle disruptions.

3.1.5 Aggregation and Disaggregation of Variables

Disaggregated and aggregated variables affect EV energy estimating methods. The same temporal or spatial resolution as the data collection experiment is used to collect disaggregated variables at fine intervals. Studies using on-board diagnostic devices often employ 1-second or finer data. Common disaggregated inputs include 1 Hz vehicle speed and acceleration [32] [33], vehicle-specific power [34] [35], kinetic energy [36] [22], road grade [37], and battery SOC [38] [39]. Some studies employ data-derived statistics like maximum or minimum speed [23].

Some variables are collected at longer intervals due to their rare changes. The rush hour index (whether a trip occurred during peak hours) [23] [40], congestion index (the ratio of idling or stops during a trip [41], road type (freeway vs. arterial) [23], and meteorological conditions like wind, humidity, and temperature [42] [43] [44] are categorical variables. Other aggregated factors include infrastructure attributes like traffic lights [40] and vehicle characteristics like weight [45]. These factors help capture energy consumption trends by providing a larger temporal or regional context. Combining disaggregated and aggregated data in EV energy estimating models improves understanding of energy consumption determinants. Summery of the energy based work based on different parameter in the last 2021 to 2025 represted in the table 3.1.

Table 3.1: Summary of Literature on EV Energy based work

Ref	Year	Drive Mode	Rule-based	Dynamics	Traffic	Environment	Component
[46]	2021	Yes	Yes	Yes	Yes	Yes	Yes
[47]	2021	Yes	Yes	Yes	Yes	Yes	Yes
[48]	2022	No	No	Yes	Yes	Yes	No
[49]	2022	No	No	Yes	No	Yes	Yes
[50]	2022	No	No	Yes	No	Yes	No
[51]	2022	Yes	No	No	No	Yes	No
[52]	2023	No	No	Yes	No	Yes	Yes
[53]	2023	No	No	Yes	No	Yes	No
[54]	2023	No	No	Yes	No	Yes	No
[55]	2023	Yes	Yes	Yes	Yes	Yes	Yes
[56]	2024	No	No	Yes	No	Yes	Yes
[57]	2024	Yes	Yes	Yes	Yes	Yes	Yes
[58]	2024	No	Yes	Yes	No	Yes	Yes
[59]	2024	No	No	No	No	Yes	Yes
[60]	2024	Yes	No	Yes	Yes	Yes	Yes

Ref	Year	Drive Mode	Rule-based	Dynamics	Traffic	Environment	Component
[61]	2025	Yes	Yes	No	No	Yes	Yes
[62]	2025	No	No	Yes	No	No	Yes
[63]	2025	No	No	Yes	No	Yes	Yes
[64]	2025	No	No	No	No	Yes	Yes
[65]	2025	No	No	Yes	Yes	Yes	Yes

Different time intervals are used to process and report aggregated variables. On-board diagnostics or GPS technology may easily gather speed and acceleration data at 1-Hz, [66] [67] which can be averaged over minutes or hours . State and local transportation authorities combine traffic flow and volume data into 5, 15, 30, or 1-hour increments. Energy estimating models benefit from these aggregated data' broader perspective on trends and patterns.

4 Modelling Scale

Applications of EV energy estimating models depend on their modelling size. Microscale models, which operate at 1Hz, are ideal for applications that need detailed vehicle dynamics and excellent control. Microscopical vehicle dynamics and real-time EV control studies like eco-driving use these models to optimise vehicle control to reduce energy consumption, especially in corridor congestion or signalised intersections. In EV routing research, microscopic models dynamically find energy-efficient routes. EV integration into traffic systems is also simulated using these models to assess energy impacts . For real-time energy optimisation and traffic analysis, microscopic models are useful due to their high-resolution data requirements. Macroscopic models explore energy consumption and driving characteristics over larger spatial or temporal scales. These models are ideal for EV energy estimates over bigger regions or durations. EV fleet management, regional charging infrastructure planning, and large-scale energy portfolio forecasts relating to EV consumption are common applications. One study created a map of EV energy usage on individual road connections using link-specific traffic patterns (e.g., average speed) and geometric parameters (e.g., number of lanes, link width) [34]. Other research has evaluated EV driving range to maintain future journeys, revealing range restrictions and EV deployment planning . Regional and national strategic planning and decision-making require these models.

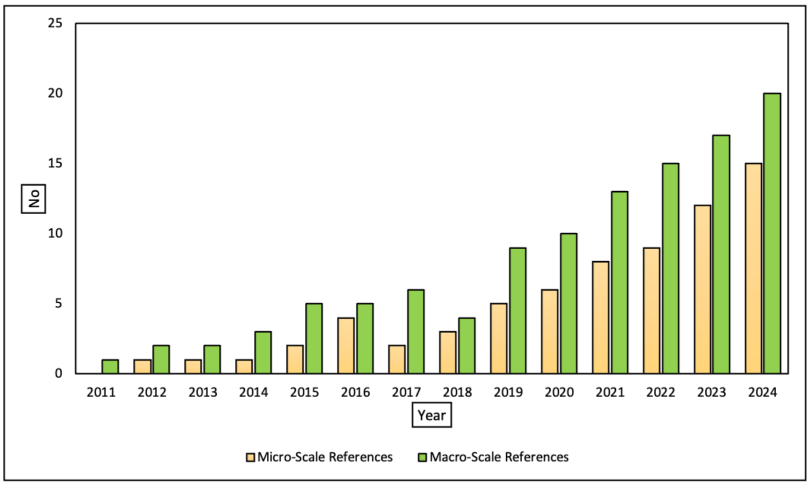

Figure 4.2: Number of publications for microscale and macroscale EV energy consumption estimation model 2011 to 2024

Figure 4.2 summarises significant studies. The data shows that EV energy consumption references have consistently climbed since 2011, plateaued between 2015 and 2018, soared in 2019, and continued to rise through 2024.

Data-driven EV energy estimation methods dominate the literature when classified by data source (real-world vs. simulation). The rise of macroscale models shows EV transportation planning and operations are focussing more on macroscopic applications.

Most studies focus on passenger cars, while transit vehicles, heavy-duty trucks, trains, locomotives, and non-road vehicles (e.g., construction and agricultural equipment) are understudied. These vehicle types only appeared in the literature after 2017, although energy consumption research has grown dramatically from 2020 to 2024, demonstrating the electrification of commercial and industrial transportation.

5 Modeling Methodology

As shown in Figure 5.3, our literature assessment indicates that the three primary techniques to EV energy modelling that are currently in use are rule-based, data-driven, and hybrid methods.

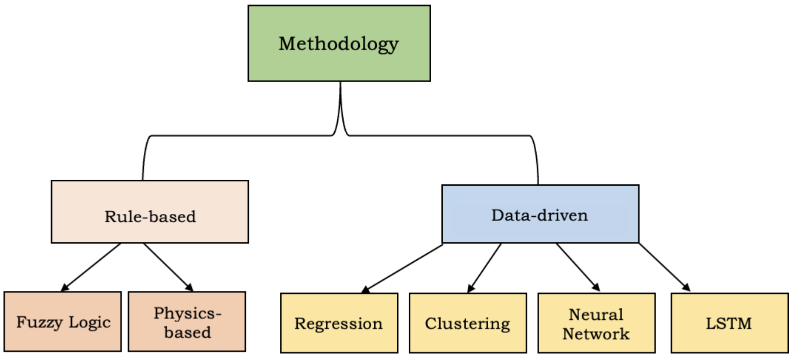

Figure 5.3: The classification scheme for the state-of-the-art EV energy modeling methods

5.1 Rule-Based

Section 2 details battery electric vehicle (EV) configuration and dynamics.The dynamics and layout of battery electric vehicles are more simple and uniform than those of internal combustion engine vehicles, facilitating better modelling. Numerous studies assess electric vehicle energy consumption at the microscale utilising Newton's law, presuming constant powertrain efficiency, or by integrating traffic and car-following dynamics. Regenerative braking is modelled via methodologies such as fuzzy logic or reduced speed-dependent relationships. Although rule-based models are simple, they frequently lack precision in particular contexts and encounter difficulties when applied to large-scale systems, such as calculating energy usage across a fleet or addressing intricate interconnections within extensive transportation networks.

5.2 Data-Driven

Improvements in sensors, automotive electronics, and telematics have increased data accessibility for electric vehicle energy modelling, facilitating the application of diverse data-driven methodologies. Multivariate linear regression is the predominant statistical method, integrating speed, acceleration, and their interactions as essential variables. With the advent of machine learning, methodologies such as artificial neural networks (ANNs) and long short-term memory (LSTM) networks have been utilised to elucidate intricate nonlinear correlations in energy consumption. Moreover, unsupervised learning techniques, such clustering and principal component analysis, facilitate data preprocessing, pattern detection, and model optimisation, hence improving accuracy, interpretability, and generalisability.

Figure 5.4 shows that EV energy consumption literature has grown rapidly through 2024, with data-driven models becoming the dominant methodology from 2015 and maintaining this trend. A closer look of research up to

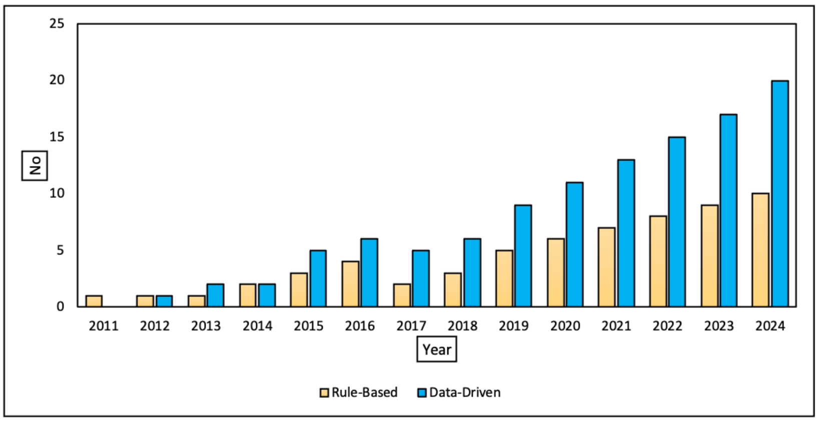

Figure 5.4: No of publication Rule-base and Drive-base 2011 to 2024

2024 shows that data-driven models for electric passenger cars, buses, and non-road vehicles are progressively calibrated using real-world data. Truck and train energy consumption modelling uses rule-based methods more often. statistics-driven methodologies now apply to powertrain dynamics, traffic statistics, driving behaviour, network profiles, and climatic variables at link-based or 5-minute intervals. Customised studies of cars, drivers, and scenarios are already common using these models. As of 2024, their substantial dependency on unique datasets still hinders generalisation across multiple situations. This constraint highlights the need for more study to increase data-driven model adaptability and scalability in broader applications.

Data-driven electric vehicle energy consumption models encounter two primary limitations: diminished performance beyond their training datasets and restricted interpretability when employing black-box algorithms such as neural networks. Hybrid approaches have been suggested to address these difficulties, integrating rule-based methods for generalisation with data-driven techniques for precision and customisation. Models such as Ye et al. [68] employ physical principles for feature selection and utilise data-driven training to enhance scenario-specific performance.

6 Discussion

Various energy consumption models are designed for particular energy-centric electric vehicle applications. Figure 6.5 depicts standard situations for the implementation of EV energy models at different scales. Energy consumption rate models are ideal for creating eco-driving systems (centred on longitudinal manoeuvres) for individual electric vehicles or for optimising environmentally friendly traffic signal control at junctions. Conversely, aggregated models are more suitable for regional electric vehicle applications that consider long-term impacts.

The findings of this review highlight several research areas that warrant greater focus in future studies.

- Contemporary research on electric vehicle energy estimation predominantly concentrates on passenger vehicles, with scant investigations into alternative vehicle categories. Nonetheless, as the electrification of goods and transit progresses, there is an increasing necessity to rectify this deficiency. Trucks account for more than 20% of overall transportation energy consumption, whereas public transit is a crucial solution for mobility issues, especially in emerging countries and densely populated regions. Further research should concentrate on precisely modelling the energy usage of electric trucks and buses to facilitate the transition to electric transportation.

- Vehicle-to-grid (V2G) technology is emerging as an economical alternative for enhancing electric vehicle utilisation and power grid efficiency. A primary issue in V2G integration is the creation of computationally efficient algorithms capable of managing real-time analysis of EV energy usage and the scheduling of large-scale charging facilities [82]. Embedded EV energy consumption models must accurately estimate and compare energy usage across diverse driving scenarios to facilitate effective decision-making in dynamic contexts.

- Multiscale models provide the benefit of encapsulating essential characteristics across various temporal and spatial resolutions, facilitating a holistic approach that synthesises data from individual vehicle components to

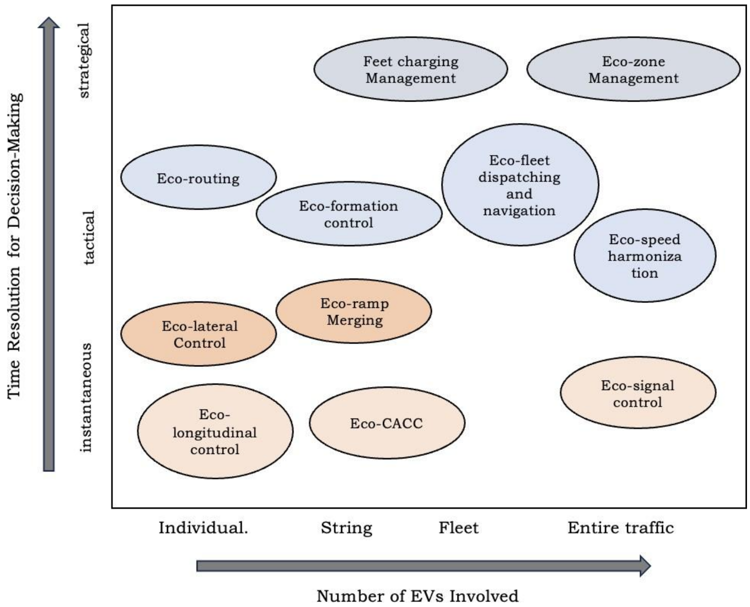

Figure 6.5: Applications of EV Energy Models Across Various Time Resolutions

extensive traffic networks. Current research has predominantly concentrated on either microscale or macroscale energy estimation for electric vehicles, resulting in a deficiency of models that deliver uniform energy estimates across various scales. Creating such models would improve precision and relevance in diverse contexts. A significant problem exists in developing algorithms or approaches that can effectively and precisely tackle the intricacies of multiscale modelling.

- Data-driven models, particularly those based on deep learning, frequently exhibit inadequate generalisation outside their training datasets. Future initiatives should concentrate on augmenting model resilience, guaranteeing representativeness in training data, and improving interpretability to render energy estimating models more transparent and practical across varied settings.

- Hybrid approaches should be further investigated to capitalise on the advantages of both rule-based and data-driven methodologies. Integrating physics-based feature selection with machine learning-driven parameter optimisation may enhance both accuracy and generalisation.

- The accessibility of real-time data from IoT devices, connected vehicles, and intelligent infrastructure offers prospects for enhancing energy calculation precision. Subsequent study ought to investigate the amalgamation of telematics, traffic sensors, meteorological data, and energy grid interactions to enhance electric vehicle energy models.

- With the growing prevalence of machine learning and deep learning in energy estimates, it is essential to integrate explainable AI (XAI) methodologies to enhance understanding of model prediction processes. This will improve confidence, interpretability, and decision-making in energy management systems.

- A common standard for evaluating electric vehicle energy estimation models across studies is currently absent. Subsequent research should focus on creating benchmarking datasets, standardised evaluation metrics, and validation methods to enable equitable comparisons and reproducibility.

By addressing these future areas, EV energy modelling can develop into a more accurate, scalable, and flexible instrument for enhancing energy efficiency in transportation and smart grid applications.

7 Conclusion

This study provides a comprehensive review of recent studies on estimating energy consumption in electric vehicles, focussing on models influenced by factors such as vehicle components, driving dynamics, traffic, and environmental conditions, as well as modelling scale (microscopic versus macroscopic) and approach (rule-based versus data-driven). The analysis encompasses data sources (simulation versus real-world), vehicle categories (automobiles, trucks, buses, trains, and non-road vehicles), and publication trends from 2011 to 2024.

Vehicle components remain essential in modelling propulsion and energy flow. Rule-based microscale models depend on these components for direct energy output calculations, whilst data-driven macroscale models are progressively integrating aggregated vehicle component data. Vehicle dynamics are a crucial element across all modelling scales and techniques. Traffic conditions are crucial inputs, functioning as a proxy for vehicle movement in macroscale models, whereas microscale models depend directly on real-time data about vehicle speed and acceleration. Environmental elements, especially road gradient and climatic conditions, are extensively utilised in macroscale models, with road gradient being a crucial component at both scales. Since 2015, data-driven electric vehicle energy estimation models have gained considerable prominence, outpacing rule-based approaches. Over the past five years (2020–2024), there has been a notable increase in the creation of macroscale models, indicating a heightened emphasis on large-scale applications such fleet management, smart grids, and transportation planning. The increasing utilisation of machine learning, deep learning, and hybrid modelling techniques has enhanced the precision and flexibility of electric vehicle energy estimation models.

While various modelling scales cater to distinct applications, recent trends indicate a significant demand for multiscale models that combine microscale accuracy with macroscale relevance. These models would ensure consistency across different spatial and temporal resolutions, hence improving the accuracy and dependability of electric vehicle energy consumption forecasts in various real-world contexts.

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