Chapter 2

Survey of Literature

2.1. Introduction

Transport is one of the most significant contributors to global climate pollution. Air pollutants emitted by gasoline and diesel powered vehicles are linked to a variety of adverse health effects, including disease. Clean and environmentally friendly vehicles can prove highly beneficial in solving this climate crisis. The need for sustainable energy has refocused attention on electric vehicles (EVs). EVs are superior to their gasoline-powered counterparts in a number of ways, including a smaller carbon footprint and reduced maintenance costs. The fact that EVs' electricity can come from a variety of effective sources sets them apart from their conventional counterparts. Furthermore, electric vehicles (EVs) are characterised by their lack of tailpipe emissions, including carbon dioxide (CO2) and other pollutants such as nitrogen oxides (NOx). Additionally, recent years have witnessed significant progress in the development of eco-friendly intelligent transportation system (ECO-ITS) technology. The implementation of these technologies has the potential to enhance the efficiency of transportation networks, resulting in a reduction in fuel consumption. The objective of ECO-ITS technologies for electric vehicles (EVs) is to enhance vehicle performance by devising novel energy management strategies for electric drive systems that are optimised using trip-specific information [2]. The notion of eco-routing navigation, which primarily focuses on identifying the best energy-efficient route throughout a journey, has also been categorised as an ECO-ITS technology. This chapter is a review of the literature concerning the eco-routing concept in EVs and its related aspects. It underlines the availability of cutting-edge techniques and their contribution to maximising energy efficiency. Range and range anxiety have also been described with respect to EVs. Eco-routing systems are mainly involved in predicting vehicle range and reducing energy consumption by locating an "eco-route." All vital factors that affect the eco-routing of EVs have been discussed. Topics related to batteries that are seen to influence eco-routing have also been presented. Existing literature has been extensively studied with a focus on the fundamental description, technological advancements, shortcomings, and various strategies for developing precise, energy-saving navigation systems.

The ruinous effect of the industrial revolution on the environment is known to all. Research on EVs has been revitalised in response to rising concerns about transportation's role as a significant contributor to global pollution. The widespread introduction of EVs can aid in recovering the losses caused by harmful vehicle emissions. Eco-routing appears to be a viable solution for minimising energy use and thereby increasing its acceptance in EVs. An eco-routing navigation system has other benefits beyond reducing carbon emissions and energy consumption. This technological idea can also be used to effectively reduce range anxiety in electric vehicles. There has been a recent rise in the prevalence of GPS-guided navigation systems in cars, which advise drivers on the fastest routes. However, energy usage and its minimisation can be considered more crucial than time in EVs. The shortest distance does not always equate to the least amount of energy consumed, as various different factors need to be considered when a vehicle manoeuvres from a starting point to a destination. Eco-routing can be effectively used in such situations, as it calculates the most energy efficient route instead of the shortest one. Numerous aspects, including vehicle dynamics, real-time traffic, and road topography, go into the development of an eco-routing system for EVs. Estimation of driving range and energy consumption are other imperatives.

2.2. Range and Range Anxiety in EVs

The EV driving range is defined as the distance a vehicle can travel using just the power from its electric battery pack to complete a specific driving cycle [5]. It is the maximum distance an EV can travel using the available energy. In case of BEVs, it means the total range per charge. EVs have minimal widespread appeal due to their high price and restricted range. EVs confront significant difficulty owing to their limited range, which is caused by the low energy density of batteries as compared to ICEVs. The extended duration required for recharging, in contrast to the relatively rapid process of fueling a tank, is a drawback, as is the current scarcity of public charging stations. A longer range would require more energy from the batteries, which would necessitate the use of larger packs, rendering the physical proportions of an EV impracticable. The range of a commercial battery operated EV is currently reported to be around 100–150 km [6]. Range anxiety is a condition that has been identified as one of the key impediments to the widespread adoption of all-electric vehicles. It is the apprehension that a vehicle will not have enough range to reach its destination, leaving its occupants stranded [7]. This anxiety may result in EV owners driving less. Richard Acello coined the term "range anxiety" in the San Diego Business Journal on September 1, 1997, in reference to the concerns of GM EV1 electric car commuters [4]. Driving experience is also considered an indicator of range anxiety. With consistent and increasing use of EVs, users become more confident in adjusting themselves to the anxiety. With the advancement of technogy,newer BEV models are introduced to the market, ranges continue to increase. Added complexity and weight diminish the electric motor range of PHEVs, making them less efficient than BEVs [6]. EV range is affected by factors such as vehicle speed, vehicle weight, road grade or elevation, driving cycle, powerful headwinds, and diminishing battery capacity. Consequently, it is generally true that EVs perform better in urban environments, and putting more emphasis on the aforementioned factors should enable EVs to travel further. Battery life and the outside temperature both have an impact on an electric vehicle's range. Air resistance increases with velocity; hence, speed matters. The right path must be taken because it significantly affects range anxiety [6]. Some experiences and media accounts have dramatically exacerbated range anxiety, and although manufacturers greatly exaggerate that the range of EVs is being expanded, it has not been very helpful in reducing consumer worry. Owners frequently make the assumption that the vehicles' range is much smaller than it actually is, which has prevented more people from adopting and using them. The three main methods for lowering anxiety brought on by restricted range are implementing energy-efficient navigation, increasing battery capacity at a cheap cost, and forecasting remaining range while travelling [4]. Therefore, effective detection of range is an obvious step forward towards acceptance of EVs. The presence of comprehensive information can play a role in mitigating concerns, as a well-designed navigation system equipped with data on battery capacity, remaining distance, and optimal energy-saving routes has the potential to reduce anxiety. The utilisation of eco-routes will thus lead to a reduction in energy consumption and a decrease in emissions on a significant scale.

2.3. Eco-routing navigation system

Eco-routing is a navigation-based automation tool. It is a relatively new idea, and research is still in the early stages. The Global Positioning System (GPS) is typically used in the development of these systems. Unlike a traditional GPS-based navigation system, eco-routing selects the most energy-efficient path, which in some cases may not always be the shortest or fastest route. It is based on the assumption that longer journey times can be exchanged for reduced consumption [8]. The majority of modern GPS-based navigation systems are designed to determine the quickest route possible. The quickest routes might suffice when ICEVs are concerned. But, taking the shortest route might not always be the most energy-efficient option, which could present problems for EVs. Range and energy efficiency are essential criteria for EVs. Therefore, creating an eco-routing system exclusively for EVS seems like a propitious objective. By assisting the driver in selecting a route that will allow the battery's available charge to cover the distance up to the destination, these systems provide a way for electric cars to lessen range anxiety [9]. These systems, while promising a reduction in fuel consumption and greenhouse gas emissions and a consequent reduction in carbon footprint for a fossil fuel-powered car, also provide means to reduce range anxiety for hybrid and electric vehicles. Recent research shows that common navigation systems are built on algorithms that take into account things like the weather, the kerb weight of the EV, real-time traffic, and a few other location-specific data points [9]. Every common eco-routing method is time-dependent, which in turn depends on how far the available routes are from the requested source to the desired destination. However, there are a number of variables that influence an EV's energy usage at a certain moment in time. To estimate energy usage precisely, a detailed model is needed. The eco-routing idea is also subject to a number of limiting assumptions. For instance, picking the same eco-route will cause more congestion and, as a result, more time and energy to be used by all cars driving between a source and a destination. Similar to how a road may be the shortest but have greater travel times due to congestion if all vehicles take it, reducing the travel times on alternate routes. Driver preference and experience plays an important role here. Driver choices where energy economy is preferred are given more emphasis. When creating an effective eco-routing system, consideration must also be given to the needs and behaviours of the drivers. When there are different possibilities for getting to the same place during a manoeuvre, these systems can estimate the most energy-efficient route. It is important to note that an eco-routing system's design takes into account all significant factors that contribute to energy consumption or loss in a vehicle and forecasts a route that will save the most energy, but it may not necessarily be the quickest. The creation of an eco-routing system requires a trade-off. But because it considerably increases an EV's range, an eco-route can be seen as essential for EV users.

2.3.1. Electric Vehicle Routing Problem

Electric vehicle energy efficiency estimation is becoming increasingly significant. As a result, the Electric Vehicle Routing Problem (EVRP) was born. Because the use of electric vehicles has lately expanded, academics from all around the world are attempting to develop effective solutions to the EV routing problem. A literature assessment of a few of the proposed routing challenges follows. Artmeier et al. (2010) focused their research on the most energy-efficient and efficient routing strategy rather than the distance traversed [10]. They proposed a solution to the Shortest Path Problem that used an energy graph to display the amount of energy consumed. The developed architecture had four distinct techniques, Dijkstra, Expand, FirstInFirstOut (FIFO), and Expand-distance , that were utilised to find the path that consumed the least amount of energy. It was the first recorded case of EVs being introduced onto the market, and one of the features was an assessment of energy consumption based on the test EV's acceleration and deceleration costs. A navigation system that uses the EVRP to find the best path has been developed [10]. The article focuses on the development of a prediction algorithm that uses remaining energy and cruising range to determine the route that will save the most energy for a given journey. The primary goals of this study were to formalise energy-efficient routing by solving a constrained shortest path problem (CSP), which is a variation of a general shortest path algorithm. The algorithm was designed with rechargeable batteries and an energy graph in mind, and it was tested using a prototype to achieve optimum energy efficiency while routing. The study takes into account the fundamental characteristics of EVS, such as regenerative braking, which increases the cruising range of existing EVs by around 20% in an urban context and by even more in mountainous terrain [10]. A few known routing methods, such as the Dijkstra algorithm, have been tested with the addition of additional factors that serve their purpose. The authors came to the conclusion that efficient routing for battery-powered EVs will be critical in the future. Conrad and Figliozzi demonstrated a rechargeable Vehicle Routing Problem in 2011. Vehicles were given time frames for the problem. Customers were allowed to recharge their vehicles at custmer locations only during that that frame. The work aimed to reduce total routing costs, including travel distance, time of service, and recharge time [11]. In 2013, Baouche et al. published a study on electric car route planning. The model was created using travel information and speed data as inputs. To encourage the use of EVs in practise, systematised tools were developed to reduce energy consumption using a dynamic consumption model [12]. Schneider et al. published their work on a vehicle routing problem in 2014, with the main goal of minimising costs when going from a source to a destination. To compute these expenditures, the travel cost was added to the fixed vehicle cost. They used a modified Clarke and Wright (1964) heuristic approach to design the initial routes, as well as a metaheuristic Adaptive Variable Neighbourhood Search algorithm for future refining of their proposed algorithm [13]. J. Lin et al. published a universal EVRP in 2015 that discovered the best energy-efficient route with the shortest travel time. The effect of vehicle load on battery utilisation has also been considered in this EVRP model. The concept used a simplified graph representation during routing and investigated both paired and unpaired delivery and pick-up activities, making no assumptions regarding vehicle size or battery capacity [14]. The EVRP's unique feature was that the energy usage from battery sources was determined not only by the vehicle's speed but also by its weight, which is based on consumer demand. Finally, it was discovered that when traffic is dynamically high, various real-time disturbances such as large traffic congestions, road obstructions, and other unusual events can render eco-routing in EVs useless. A solid EV routing system is required for EVs to be broadly adopted for commercial use. A. Afroditi et al. demonstrated an EVRP with industry restrictions in 2014. It investigated the topic of EV routing and scheduling. The Capacitated Vehicle Routing Problem was employed as a framework to help them achieve their goals. The EVRP was modelled using a rigorous mathematical formulation, and numerous constraints, like capacity limitations and the vehicle's predetermined charge level, were noted. In addition, historical EVRP patterns were examined in order to design an effective solution technique. The researchers created a detailed mathematical model that takes into account the problem's realistic limits in terms of electric vehicles [14]. In 2020, Wu et al. published a work that intended to determine the feasibility of calculating an eco-route as well as extend the driving range [2]. They demonstrated an algorithm for energy estimation of a route, and their results showed that an energy efficient route could save about 50% more energy as compared to traditional methods.

2.3.2. Current primary eco-routing methods

A review of the literature on eco-routing techniques now in use reveals that the majority of eco-routing navigation models created up to this point have been based on three well-known eco-routing techniques. The first technique is one that Barth et al. suggested. It is the first known instance of an eco-routing technique that has been published, and it uses a model called the Comprehensive Modal Emission Model (CMEM) to assess both the quantity of emissions and fuel consumption of moving objects [15]. The consumption of fuel can be approximated using equation(1)

$$\ln(f_k) = \beta_0 + \beta_1 v_k + \beta_2 v_k^2 + \beta_3 v_k^3 + \beta_4 v_k^4 + \beta_5 s_k \tag{1}$$

where v_k is the average speed of traffic and s_k is the road elevation. Multivariate nonlinear regression was used to acquire the coefficients [16]. The β-coefficients were acquired using the method of multivariate nonlinear regression. An actual traffic information system provides the average speed. The second method is the one that Andersen et al. described [17]. Eco-routing is made possible by the system using GPS data and vehicle fuel usage information. The average consumption recorded on each road is assigned by the function f_k that was obtained. Jurik et al. suggested another technique where while modelling the system, the method accounts for losses brought on by changes in altitude, losses from friction, and aerodynamic drag [18]. The function can be expressed as

$$f_k = \{E_r + (\alpha - 1)E_p\} \; if \; E_p \le 0$$
$$and \tag{2}$$
$$f_k = \{E_r\} \; if \; E_p > 0$$

Where E_r stands for losses resulting from aerodynamic drag and rolling friction, E_p is a potential energy, and, α, a constant, reflects the ability of the vehicle to recover after experiencing those losses. The E_r and E_p values depend on variables like the average speed, the length of the road, and a few additional characteristics unique to each vehicle.

2.3.3. Existing eco-routing prototypes

A survey of the literature reveals that several different approaches to determining an ideal eco-routing system have been published to date. These systems employ various analytical models and tools and are based on many parameters that influence energy usage and aid in the identification of the eco-route. Several papers have been published that contribute to the development of an effective eco-routing navigation system, thereby improving an EV's necessary range and energy efficiency. The CMEM is one of the first known systems for estimating a vehicle's power consumption and emissions [15]. Andersen et al. suggested an eco-routing technique based on GPS data and fuel usage from comparable vehicles in 2007 [17]. The technique proposed by Jurik et al. in 2014 takes into account losses caused by changes in elevation, friction losses, and drag force when simulating the system, allowing for eco-routing [18]. Several solutions have been proposed for the electric car routing challenge. Conrad and Figliozzi demonstrated a rechargeable Vehicle Routing Problem in 2011 [11]. Claire F. Minett et al. developed an eco-routing system based on speed profiles in 2011. Traffic pattern-based speed profiles are synthesised and input into the basic power based model (VT-CPFEM-1) [8], a vehicle energy consumption model. Schneider et al. published a vehicle routing problem in 2014, with the main goal of minimising the sum of the vehicle and trip costs [13]. Richter et al. published a model based on the electric vehicle's time of traverse and route energy consumption in 2012 [19]. M. Kubicka et al. published in 2016 that an eco-route can be produced by utilising an on-board GPS tracker that computes the most energy-efficient path depending on road network circumstances at the time the driver is about to begin a trip [16]. The approach was created by employing shortest path routing algorithms such as Dijkstra's algorithm.

a. *Depending on the speed profiles*

In 2011, Claire F. Minett et al. attempted the estimation of an eco-route using digital mapping features. A research programme was created that used previous link speed data as a foundation for recreating speed profiles, allowing fuel costs per link to be calculated [8]. The traffic pattern based speed profiles that were obtained were then fed into a vehicle energy consumption model called the simple power-based model (VT-CPFEM-1). The fuel costs obtained were allocated to links on the basis of the time expected to travel for that link. As demonstrated by the obtained speed profiles, this work successfully indicated that the vehicle's fuel usage is influenced by factors like vehicle speed and acceleration. It was also highlighted that location-based attributes affect the speed profiles of a route, meaning that information from maps can be quite efficiently used in eco-route development.

b. *Depending on historical and real-time traffic information*

Growing environmental concerns have sparked the development of numerous strategies to improve the energy efficiency of vehicle travel. The construction of an eco-routing system that finds the least energy-intensive way between two places along a path, where one is a source and the other a destination, is the focus of this study. The method is based on both historical and real-time traffic data gathered from a variety of data sources. The most energy-efficient routes have been determined using algorithms for shortest path routing. A vast information database for calculating energy usage has been combined with a microscopic emissions model by researchers in this field to produce hybrid techniques [20]. In their study of motorway-only networks, Barth and Boriboonsomsin calculated the amount of gasoline used and released for each motorway connection using the average traffic speed determined by a traffic performance measuring system [3]. The system was composed of a routing engine, an algorithm for calculating the best route, a database called "DynaNet" that uses a fusion algorithm based on traffic information gathered both in real-time and offline from multiple data sources, a database of energy consumption estimates for various car types under varying road and traffic conditions, and a user interface for receiving and displaying the driver's source and destination preferences.

An energy-optimal real-time navigation system (EORTNS) is described in a different strategy of the same type [21]. Based on the real-time traffic information system given by real-time traffic information systems like SYTADIN, it is a more recent version of the Optimal Real-Time Navigation System (ORTNS) [21]. The entyrely independent system provides the user with a real-time energy-efficient route update and collects real-time traffic data from SYTADIN. The model in this study is a network of roads with intersections and the edges of the road sector as its vertices. The energy needed to move the vehicle through the designated segment, as calculated at query time, is represented by the costs of the edges. To find the ideal eco-route, a shortest-path electric car routing issue is used.

c. *Based on GPS and fuel consumption data*

Eco-routing authorises drivers to traverse the most energy-efficient route during a particular manoeuvre. The EcoTour system was developed by O. Anderson et al. They devised a model using GPS data and vehicle fuel consumption values. The model was created by allocating weights to relevant characteristics. An arbitrary source-destination pair was considered while the task was performed in Denmark. It was determined that EcoTour could be programmed to yield the fastest, shortest, and most energy-efficient route, as well as statistics for all three routes [17]. Another work that implemented fuel data described how software-based OpenStreetMap (OSM) with eco-weights derived from global navigation satellite system (GNSS) CAN bus data enables eco-routing [21].

d. *Depending on time of travel and the route energy consumption*

According to studies, there are a number of criteria that must be taken into account while calculating an eco-route. These include data on traffic, the state of the roads, the weather, the number of vehicles on the route, and the drive system of the vehicle. The energy-saving potentials of several categories of EVs were displayed in a paper by Richter et al. To find eco-routes or optimum time routes, the amount of travel time and energy spent along the way were taken into consideration [22]. In order to find the eco-route, they used quick genetic algorithms as the ant colony optimisation method. The trials were conducted in 2012 using ULTraSim, a simulation programme created by the Institute of Energy Conversion and Storage. [22]. A comparison of the time and energy-efficient routing of various types of vehicles in inner-city traffic was offered in their paper. The fact that each type of vehicle produces a different eco-route shows that eco-routes are drive-specific. The findings also demonstrated that, when eco-routes are taken into account, there is considerable potential for energy efficiency. The research also indicated that the edge weight generation approach might be used to calculate the eco-route based on trip time for increased traffic density.

2.3.4. Future of eco-routing

Eco-routing in electric vehicles may appear to be a viable solution to pollution problems, but it has been observed that current eco-routing methods tend to select longer routes. Some systems are offline and founded solely on data gathered onboard a particular EV. Others may be termed online or cooperative, in which an EV shares data with other vehicles of the same class. Research is being conducted to create more advanced navigation systems. As more vehicles input traffic information, a given eco-routing system can become more accurate as more vehicles utilise it. Currently, the design of the majority of eco-routing systems does not account for a crucial factor termed road grade. It has been observed, however, that road grade plays a positive role in increasing power usage of a vehicle and should therefore be taken into account when devising better and more efficient systems. Efforts should be made to develop an EV navigation system that takes into account all relevant aspects of energy consumption and range.

Eco-routing navigation enables numerous research avenues. The development of an eco-routing system by considering all factors responsible for energy consumption shall enhance energy efficiency and reduce range anxiety. Calculations performed during the design phase enable estimation of the vehicle's tractive effort and other data, including energy usage. Future work includes the creation of a model that incorporates the effect of crosswinds on traversal. The actual EV energy usage is based on factors, many of which are hard to measure physically. Therefore, a neural network-based predictive control model to forecast the EV's energy consumption and utilisation can be developed. In addition, driving cycles significantly impacts range detection of the vehicle. These driving cycle patterns can be used as intelligent inputs to the EV to assist in making the vehicle autonomous, thereby enhancing energy efficiency. Additionally, the ecorouting navigation system can be used to determine the optimal placement of charging stations along a route.

2.4. Importance of energy consumption in eco-routing navigation systems

Inadequate operating range is a significant factor impeding the widespread adoption of electric vehicles. The focus is being placed on accurate detection of the EV range. Predicting the remaining range is a complex issue that is affected by numerous stochastic factors as well as vehicle-specific variables. Accurately detecting the range will facilitate more efficient energy consumption and reduce "range anxiety." That would be of great assistance in the development of the optimal eco-routing navigation system. Literature review reveals that, as a step towards EV range detection, models have been used to determine the remaining range based on road information. These models' specifications were derived from both genuine on-road testing on public roads and laboratory dynamometer testing. According to the authors, energy consumption has been calculated based on driving pace under various conditions with an error of no more than five percent [23].

When estimating the range of electric vehicles, an efficient energy consumption model is of paramount importance, and the first stage in the development of an eco-routing system is the accurate detection of the electric vehicle's range. A model of energy consumption should include models of road load, battery, powertrain loss, and regenerative braking from the vehicle tyre to the battery [24]. Literature demonstrates that the majority of navigation systems base their models solely on distance. Nevertheless, distance is not the only factor that affects the energy consumption of an EV.

a. **Road type:** Driving patterns vary according to road type. Depending on the road type, an EV's energy consumption will vary significantly. The vehicle's dynamics will vary depending on the nature and surface of the road. Also, driving on the highway will yield distinct results than driving in the city. On highways, it is necessary to travel at fast speeds. In contrast, travelling in the city necessitates frequent stops due to traffic and more idling.

b. **Vehicle weight:** Another determining factor is the weight of the EV. The greater the weight of the EV, the greater is the power and energy requirement. Consequently, conditions such as passenger weight and cargo weight must also be taken into account.
c. **Road grade:** The road's gradient is a contributing factor to energy consumption. When calculating energy consumption or effective range, the road grade is typically disregarded in the majority of studies. A steeper road requires more strength to surmount the effects of gravity. This increases the energy consumption significantly. When travelling downhill, vice-versa occurs.
d. **Traffic conditions:** City traffic affects the energy usage of an EV. Stop-and-go motions consume and squander more energy.
e. **Driving cycle:** The pattern at which the vehicle is being driven also contributes to the energy being consumed. Travelling at higher speed will result in more energy being consumed.
f. **Weather conditions:** Winds contribute significantly to the increase in energy consumption. Headwinds increase energy consumption because the EV must exert more force to overcome the resistance. Crosswind is another factor that must be taken into account for accurate energy consumption calculations. Auxiliary loads, such as the use of air conditioning, enhance the consumption of power.

A number of variables, including travel, the environment, traffic, road conditions, and driving habits, may affect how much energy an EV uses. Some of these elements are more important than others. The majority of the time, factors connected to travel examine the distance between the source and destination pairs as well as how frequently the EV has travelled during that time period. Vehicle parts, including the engine, speed, and acceleration, are considered vehicle-related factors. Roadway-related information, such as road surface textures and road slope, is provided by roadway factors. Significant weather-related aspects in the energy consumption model are the influence of the wind, the temperature, and the humidity. Driving habits and driving behaviour are factors connected to drivers, whereas traffic elements include traffic flow and traffic signalling [25]. The research on fuel consumption of a vehicle that has been published is summarised in Table 2.1 in order to allow for accurate range estimation and the creation of an effective eco-routing navigation system.

Table 2.1 Summary of literature on various fuel consumption models as well as techniques.

Factors	earch Respublished	Year of Publish	Summary
Travel	Ahn and Rakha[26]	2008	Analyses of the effects on fuel consumption when various route options are offered. The CMEM model provides the basis for the work.
	Frey et al. [27]	2008	Validation of actual impacts of driving cycles on the fuel consumption.Field tests were run on different routes for obtaining results.
	Boriboonsomsin and Barth [3][28-29]	2008-2012	The work involves design and development of eco-routing systems using advanced technologies to find routes that minimize fuel consumption.
	Barth et al. [3]		
Weather	US Environmental Protection Agency[30]	2015	States energy consumption improvements based on weather.
Vehicle	Joumard et al. [31]	1995	A model was proposed based on acceleration and speed of vehicle.
	Ericsson[32]	2001	Studied effects of independent driving patterns.
	El Shawarby et al. [33]	2005	Analysed how fuel consumption is affected by speed and acceleration of the vehicle.
	Ben et al. [34]	2013	Determination of fuel consumption and its analysis on basis of engine size, type of fuel used, power and speed of the vehicle
Roadway	Renouf [35]	1979	Analysis of horizontal curvature of roads on fuel consumption.
	Biggs [36]	1988	Studies related to fuel economy. Results have shown that hilly terrain consumes more energy than flat topologies.
	Pan [37]	2005	
	Boriboonsomsin and Barth[3]	2007	
	Kamal et al. [38]	2011	Development of an eco-driving system to run on slopes based on model

			predictive control.
	Wang et al. [39]	2014	Optimization of fuel consumption in slopes using local and global optimization methods.
Traffic	Biggs[36]	1988	Study of effect of traffic information on fuel consumption.
	Rakha et al. [40]	2000	Evaluation of impacts of traffic signals on consumption of fuel by using VT-Micro model.
	Sanchez et al. [41]	2006	Investigated how fuel economy is improved by good interaction skills between driver and traffic lights.
	Tielert et al. [42]	2010	Studied on impact of road traffic- to -vehicle communication on consumption of fuel.
	Asadi and Vahidi [43]	2011	Quantification of traffic signal information using predictive cruise control method.
Driver	Evans [44]	1979	Studies depending on different driving behaviour as well as different driving patterns.Results showed that aggressive driving consumes more energy.
	Ericsson [32]	2001	
	Mierlo et al. [45]	2004	
	Sanchez et al. [41]	2006	
	Taniguchi [46]	2008	
	Beusen et al.	2009	Studies on how trained eco-driving drivers helped in reducing fuel consumption of vehicles.
	Kamal et al.[38]	2011	Studied the nature of eco-driving process under varying road traffic environments and different driving patterns.

2.4.1. *Factors affecting energy consumption in EVs*

A body in motion experiences many forces, all of which add to the energy needed for themanoeuvre. The various forces that affect a moving vehicle have been illustrated in Fig.2.1.

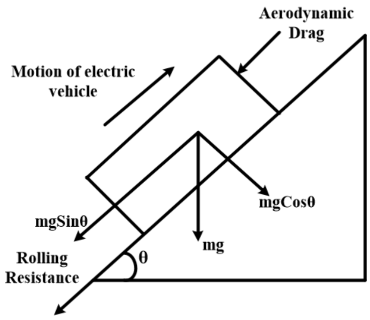

Fig. 2.1 Forces acting on a vehicle in motion

a. *Road-related information*

i. Aerodynamic drag losses

An EV when traversing at its maximum speed experiences zero acceleration. Aerodynamic drag force and rolling resistance force together make up the force required to overcome this circumstance. Aerodynamic drag force is the opposing force an item experiences when moving through the air [47]. In the case of an EV, it is the force that prevents the car from moving forward.

$$Drag\ force = F_{drag} = \frac{1}{2}\rho_{air}\, C_{drag}\, A_{frontal}\, v^2 \tag{3}$$

Where ρ_{air} is density of air (kg/m^3), C_{drag} represents drag co-efficient of the EV, $A_{frontal}$ is frontal vehicle area (m^2) and v is the velocity of the EV in m/s[47]. When a vehicle travels at higher speeds, the aerodynamic drag force tends to increase with the square of speed and becomes a significant influence. In an electric vehicle, a reduced drag coefficient improves fuel efficiency, enhancing the vehicle's overall performance. Shape drag and skin friction are the two causes of drag. When a vehicle begins to move, air in the front is pushed forward. Because the air cannot get out of the path right away, it builds up pressure, which results in high air pressure. The air behind the vehicle cannot immediately fill the space it creates when moving ahead, which results in a low air pressure area at the back. As a result, the motion creates two pressure zones that drag and push a moving object backward and forward, respectively. Shape drag is the term used to describe the overall resulting force. Near the skin of the vehicle, air practically moves at the same speed as the vehicle. Air molecules move between these speeds at a range of rates. The velocity difference between two molecules of air, or skin friction, is the second component of drag. The air pressure difference brought on by the drag force when a vehicle is moving is seen in Fig. 2.2. The vehicle's frontal size and drag coefficient have the biggest effects on aerodynamic drag. The air density is largely regarded as a constant [23] and depends on the surrounding temperature, pressure, and relative humidity. It is so because, at high temperatures, humidity has no effect on air density. It varies in direct proportion to the vehicle's aerodynamic drag force. Both the air density and the air pressure will drop as the temperature rises. The aerodynamic drag increases with the square of the velocity. Even though it is deemed insignificant in city traffic, a vehicle going at a high speed has more energy loss, with drag force being responsible for the majority of it. Crosswinds and headwinds also significantly increase drag. Drag is mathematically proportional to the product of the drag coefficient, C_{drag}, and the frontal area, $A_{frontal}$, of the vehicle. It can thereby be reduced by making the vehicle thinner and flatter with a frontal area as reduced as possible.

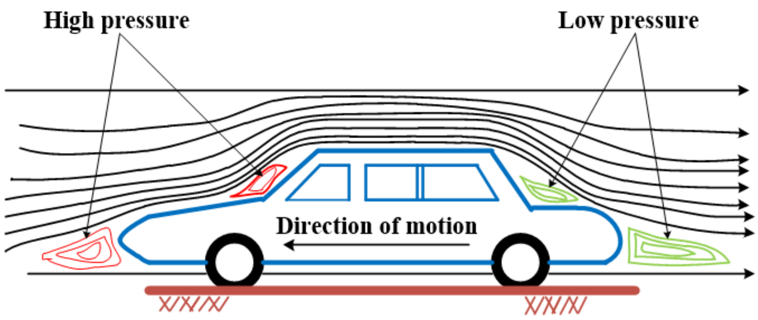

Fig. 2. 2 Aerodynamic drag forces acting on a vehicle in motion[49]

ii. Rolling Resistance

Rolling resistance refers to the counteracting force experienced by a moving object in contact with a surface. Upon the release of pressure, a portion of the energy required for motion is dissipated and unable to be fully recuperated [48]. The presence of rolling friction hinders the forward motion of the car, hence resulting in an increase in energy consumption of the EV. Hysteresis in tyre materials is the principal determinant of the reduced rolling speed of tyres on hard surfaces. This phenomenon arises due to the deformation of the tyre surface during its rolling motion. Different pressures exist in the contact area's leading and trailing portions. This action causes the ground reaction force to advance. Fig.2.3 depicts the resistance created by the deflection of the tyre as well. When the ensuing ground reaction force moves forward, it produces a rolling resistive moment. The rolling of the wheel requires a force, F operating on the centre of the wheels which will counteract this rolling-resistance moment. This power can be characterised as

$$F = \frac{R_r}{r_d} = \frac{Na}{r_d} = NC_{rr} \tag{4}$$

This moment can be replaced by horizontal force acting in the centre of the wheel and opposes wheel movement [49]. This comparable force is referred to as rolling resistance and has a magnitude of

$$F_{roll} = NC_{rr} \tag{5}$$

Where F_{roll} is the rolling resistance force, C_{rr} is the co-efficient of rolling resistance and N is the force which acts normal to the tyre rolling surface. On a paved road, a rubber tyre will experience greater rolling resistance than on a gentler road. Additionally, sand is more resistant than concrete floors. The rolling resistance of a vehicle has a substantial influence on its motion and, consequently, its energy consumption [49]. EV tyre rolling resistance losses are proportional to the force required to surmount tyre friction.

$$P_{roll} = M_{Gr.veh}\, g(R_0 + vR_1 + v^2R_2 + v^3R_3)v \tag{6}$$

Where $M_{Gr.Veh}$ the gross vehicle mass in kg, g is acceleration due to gravity in m/s^2 and R_0, R_1, R_2, R_3 are the co-efficients of rolling resistance.

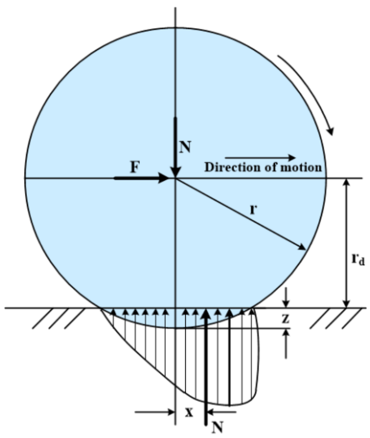

Fig. 2.3 Rolling resistance force on tyres on a hard surface [49]

iii. Road Elevation

The gradient present on a road has a significant impact on energy use. The fluctuations in velocity and acceleration of an EV demonstrate this. Levin et al.'s work demonstrates how road elevation might affect network-wide energy usage in automobiles [50]. The researchers used energy consumption models based on road load calculations, elevation data from digital mapping sources such as Google API, and an assignment model to determine the consequences of EV drivers' choices based on road traffic conditions. The results showed that the gradient of a road should not be ignored in order to find the least energy-consuming option. PAMVEC, a vehicle energy consumption modelling tool, is based on expressions derived from road load equations. The results of this tool demonstrated that vehicle energy use can be significantly altered, even when routes appear to be quite flat. The change in energy efficiency caused by road elevation is neither symmetric nor obvious, and it is determined by the average path gradient whether individual vehicle energy consumption will grow or decrease. Levin et al. projected that roads with higher road slopes would produce more variable results and consume more energy [50]. The road's slope or gradient is represented in Fig. 2.4. Here, l represents the length of the slope, d is the length of the road, h represents the elevation present in the road, and is the angle of inclination.

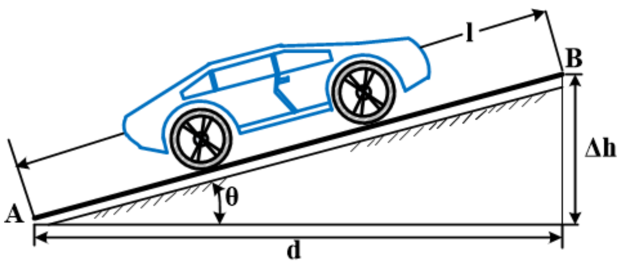

Fig. 2.4 Illustration of road grade when a vehicle is traversing uphill

iv. Traffic Information

According to research, traffic conditions have an important effect on the energy usage in EVs. Although, in a state of inertia, an EV utilises significantly less energy than an ICEV, they tend to increase if additional loads are high. More traffic would necessitate that the EV travel at a slower speed and spend more time on the road. Additionally, the vehicle flow on the road becomes sluggish, causing significant inconvenience for drivers. The road segments where traffic data is collected will contribute to traffic congestion along the travelled route. It may also result in the formation of a complete obstruction. Reducing pace may result in a significant increase in travel time, which would be a hindrance in determining the least energy-intensive route.

b. Battery-related Information

Electric vehicles are rapidly establishing themselves as the new-age solution to the problem of environmental pollution. EVs have a number of advantages, but it is believed that the batteries that power them are limiting their use. The battery life has a significant impact on the vehicle's energy use and range. The current state of battery technology is one of the main barriers to the widespread use of EVs. Assuming a practical figure of 0.25 kWh/km for the stored energy demand for a conventional passenger vehicle, a modest 200 km acceptable range would require the storage of 50 kWh of electrical energy. Thus, it would require roughly two tonnes of current lead-acid batteries, which seems unfeasible [50]. In-depth research has been conducted to increase battery capacity and longevity. The majority of lead acid battery-powered EVs have ranges that are remarkably lower than what most EV consumers consider tolerable. This is true for other battery types as well. With advancements in research, battery performance has improved but it still needs improvement in terms of enhanced battery capacity and battery life. The average battery capacity of Lithium ion batteries is around 40 kWh though there are batteries with capacity increased to about 100kWh. Battery capacity plays a direct impact on range. For instance a 40kWh battery in a Nissan Leaf EV model can give a range of approximately 250 kms. Increasing this capacity will drastically increase the range but shall aslso increse the size of the battery which in turn will lead to more energy usage. Enhancing battery performance, expanding battery capacity and managing battery size are aspects that urgently require research. Therefore, researchers can forecast and perhaps resolve the aforementioned problems by modelling the battery. Numerous battery models have been proposed over the years to aid in both the prediction of battery behaviour and the use of batteries in electric vehicle technology [51]. To guarantee that the battery operates effectively, it must be ensured that its capacity is used appropriately. When creating battery models, the following factors should be considered, as they play a key role in determining battery capacity:

i. Internal Resistance

An essential consideration for electric vehicles is the battery source. Materials with resistivities greater than zero are used to make batteries. Batteries include internal resistances in addition to pure voltage [52]. Fig. 2.5 depicts the internal resistance that is present in batteries. As technology advances, newer technological specifications for the battery are being established. A battery with low internal resistance is preferred by the majority of digital applications. Internal resistance often varies during charging and discharging based on the battery's state of charge (SoC). As it amplifies, the rate at which the battery's energy is converted to heat rises, decreasing the battery's efficiency and thermal stability. A battery's internal resistance is also thought to have a significant impact on how long it can last. A battery with a high internal resistance can change the supply voltage, which is then reflected in the load pulses. The voltage is pushed towards the end of the discharge line as a result, leading to an early cut-off [32].

ii. Open circuit voltage (OCV)

An electrochemical device called a battery creates a potential difference by combining metals with various affinities in an electrolyte, an acidic solution. The type of metal used and the electrolyte have an impact on the open circuit voltage (OCV) that results from this reaction. The battery terminal voltage is what is present when the internal equilibrium of the battery is reached in the absence of a load [53]. The OCV is depicted in Fig. 2.5. It consists of elements including SoC, temperature, and the battery's history of charges and discharges, or the hysteresis effect. OCV can be expressed as a non-linear monotonous function of SoC that takes temperature and hysteresis into account. In contrast to SoC, temperature has almost no impact on OCV unless it is extremely high. The hysteresis effect is caused by the battery voltage rising over the OCV for a known SoC while charging and falling below the OCV for that specific SoC during discharge, despite adequate relaxation time having passed.

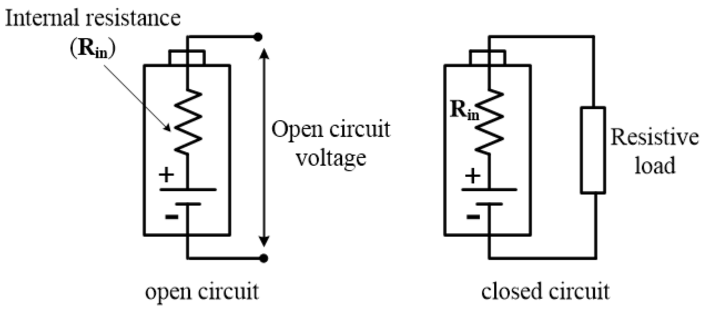

Fig. 2.5 Schematic of a battery

iii. Battery capacity

Battery capacity is the quantification of the charge banked in a battery. It is based on the amount of active material in the battery source [39]. It is often measured in Ampere hours and depicts the maximum amount of battery energy that can be drained to power an EV under specific conditions. The actual scenario may differ slightly because the battery's energy storage capacities may differ dramatically from the nominal capacity rating. This capacity is highly influenced by the battery's age, charging or discharging routine, and temperature. A battery's capacity varies with current discharge rates and dynamic characteristics [54]. If the discharge rate is kept low and dynamic, there is a large increase in available battery capacity. It should also be noted that the operating temperature of some types of batteries is proportional to their capacity. This phenomenon is modelled by Peukert's equation [11].

$$I^n \times t = C \tag{7}$$

where C is the capacity of the battery (Ah) with a constant load current I (A), t is the total discharge time for one battery cycle, and η is the Peukert’s constant. The preceding equation is only applicable when the current or temperature are both constant. Temperature is a crucial factor in determining the correct capacity of lithium ion batteries.

iv. Coulombic Efficiency

Coulombic efficiency (CE), also known as faradaic efficiency or current efficiency, is the proficiency with which a battery transfers charge or electrons [55]. CE is a computed ratio of total charge retrieved from the battery to total charge placed into the battery over the duration of a full cycle [56]. The efficiency of batteries is a crucial parameter, particularly when large battery systems are involved, such as in electric vehicles (EVs), energy storage systems (ESS), and satellites. This efficacy can be calculated using coulombic efficiency. The CE of lead-acid batteries is approximately 90%, while nickel-based batteries have even lower Ces. Li-ion batteries have the highest efficacy ratings among rechargeables. It is claimed that they offer nearly 99 percent efficiency. This is only possible when the battery is charged slowly and at low temperatures [55]. The coulomb counting method is regarded as one of the most precise methods for calculating CE. It provides vital information for determining the state-of-charge (SOC) of a battery, which is an effective method for determining the EV range. The coulombic efficacy of a battery can be determined by observing its charging and discharging behaviour over a number of operation cycles [57].

v. Temperature effect

The temperature effect has a significant impact on battery OCV [55] and capacity [57]. Typically, battery capacity is measured at ambient temperatures. The available capacity is directly proportional to the change in temperature, but is diminished below 20 degrees Celsius [53]. The internal resistance of a battery is also affected by changes in temperature. Temperature has an effect on the amount of charge drawn from a battery. Typically, higher temperatures result in greater battery capacities. In an effort to maximise battery capacity, however, intentionally increasing battery temperature is not a recommended strategy because it reduces battery life. The increase in temperature within a battery excites the electrons, resulting in a reduction in internal resistance, which permits a greater current draw. In contrast, a temperature drop below -10 C significantly reduces energy and power capacity, particularly in Li-ion batteries [58]. In EV and HEV applications, thermal modelling for predicting the temperatures of a battery undergoing different charging and discharging cycles may be useful in resolving battery-related problems. For example, a simple first-order thermal model with only two parameters, namely thermal capacity and heat conduction coefficient, can be incorporated [59] if it is suitable for the purpose.

vi. Ageing effect

The age and history of the battery strongly impact battery capacity. Depending on vital characteristics such as energy capability or power capability, a battery's age can be indicated by a decline in capacity or an increase in internal resistance [59]. Capacity fading is the depletion a battery experiences after a certain period of use or storage. The capacity decline is a permanent loss. End of life is the term used when only around 20 % of nominal battery capacity is available [53]. The majority of the battery ageing process can be classified as calendar life, which is caused by a long term storage induced capacity loss and cycling, which includes capacity loss because of repetitive battery utilisation and battery chemistry specific effects such as sulfation.

2.4.2. Generalised estimation models

a. Road Load Model

The movement of an automobile is regulated by road terrain dependent factors like rolling resistance, aerodynamic drag force, acceleration force, road load and road gradient as shown in Fig.2.6 below.

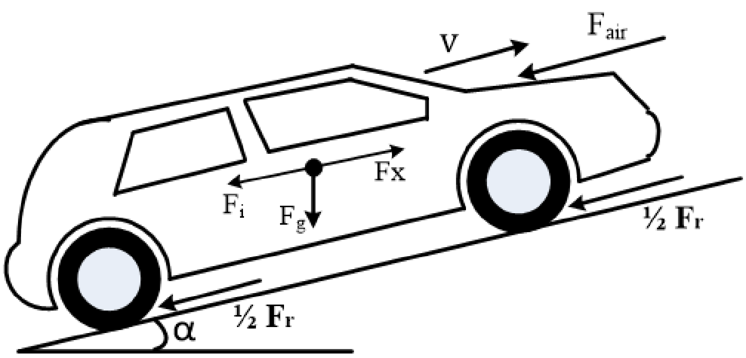

Fig. 2.6 Various components of force acting on a vehicle

The equation for tactive effort of the vehicle can be written as[60]

$$F_x = F_r + F_{air} + F_g + F_i \tag{8}$$

Here, F_x is the force propelling motion, F_r is the rolling resistance force, F_{air} is the aerodynamic drag force, F_g is the force owing to road grade, and F_i is the vehicle inertia force.In addition to the coefficient of rolling resistance, the vehicle mass, the gravitational acceleration, the density of air at room temperature, the drag coefficient, vehicle frontal area, vehicle speed, incline on the road, and the vehicle's acceleration are also considered. Therefore, road information, driving conditions, information related to the vehicle like its weight, tyre pressure and meteorological conditions play a pivotal role in the development of this model [60].

b. Powertrain Loss Model

According to J. Wang et al., a vehicle's powertrain included an inverter, a 200-200W AC induction motor that is water-cooled, and a reduction gear [23]. A dynamometer-based test setup was built, and it was used under strict laboratory circumstances to determine the system's loss of power. To conduct the experiment and determine the power loss incurred while the car is manoeuvring, the inverter signal was varied. The outcomes were then processed for various driving speed values. According to the analysis, the same motor behaved significantly differently when functioning in the traction mode and when engaged in regenerative braking mode. The power loss was calculated using a MATLAB tool as

$$P_{loss} = 0.21T^2 + 0.0097|T|\omega + P_c \tag{9}$$

Where, T is the motor's torque, ω is its angular speed, and P_C is the motor's power loss in idle mode. According to the findings, powertrain efficiency for a given motor output is lower when the motor operates in regenerative braking mode than when it operates in traction mode. Rakha et al. provided information about the INTEGRATION programme in 2012 with the intention of promoting eco-routing [61]. It is a 10 Hz vehicle simulation programme that uses traffic data gathered from numerous sources to monitor moving cars [61]. The model also accounts for lane changes and collisions that occur throughout a journey. Based on anticipated fuel consumption, roads are designed for cars to travel over specified designated route links. Each car uploads its fuel consumption data on a single route connection when a trip is complete, which aids in continuously improving the predictions. It is based on observations made about similar classes of vehicles.

c. Regenerative braking model

Regenerative braking in the case of EVs can be considered a salient part of the EV drivetrain's efficiency. It is a technology that can recover used energy in electric vehicles. It transforms a vehicle's kinetic energy into either a readily usable form or can even be retained until it is required. The propulsion motors use the momentum produced during braking to recuperate energy that would otherwise be lost as heat. This is distinct from the conventional braking of internal combustion engine (ICE) vehicles, in which the vast majority of braking power is lost as heat. This form of braking increases the vehicle's overall efficiency by reducing energy consumption, and it also extends the life of the vehicle's braking system. Regenerative braking-based braking technologies are typically vehicle-specific. In their research, Wang et al. [23] examined two strategic models of regenerative braking: a parallel regenerative braking control strategy and a one-pedal driving control strategy. These strategies depend on the parameters of the EV's total force when the brakes are ON and its regenerative braking force. The formalisation of the regenerative braking model is based on the distance the brake travels after being applied. In the case of hydraulic brakes, a portion of energy is always lost as heat, and the braking force is not proportional to the distance the brake pedal travels. The one-pedal strategy, which aimed to improve vehicle performance, mitigated the drawbacks of this approach [23]. Unless there is an emergency, only one implement, the accelerator pedal, is used. The algorithm utilises the deceleration from the accelerator pedal itself, rather than the braking lever. The energy efficiency determines the energy consumption, which in turn aids in the estimation of the remaining range of the vehicle.

d. Cruise Control Model

Cruise control is a technology that regulates the pace of a vehicle automatically. This automated system is powered by a mechanism that regulates the car's throttle so that it is driven at a constant speed as determined by the vehicle's operator [62]. A cruise control system can be relatively straightforward to model. If rolling friction is regarded as opposing vehicle motion and the inertia of the EV's wheels is ignored, the system can be reduced to a simple mass and damper system. A model with cruise control can also be designed to reduce energy consumption and increase the EV's efficacy. In 2012, Oorschot et al. published research demonstrating a control model for the Lupo EL. The original sport position of the gear selector was utilised to implement the cruise control system [59, 63]. Multiple safety mechanisms have been implemented as control measures if the brake lever is ever depressed while the control system is in the on position. Two mechanical brake switches and a pressure sensor estimated the system brake application [62]. A high-precision GPS sensor was utilised to obtain elevation data.

e. Traction Control Model

A traction control system design is aimed at preventing road-driven vehicles from losing traction. When the input to the EV and the corresponding torque do not match the road surface conditions, control is required. The development of an algorithm to represent traction control assisted in optimising the vehicle's speed and stability on slippery surfaces [59]. In this model, the algorithm is so designed that the logic controller can set throttle limits for the inverter. Thus, the traction could be regulated by rescaling the original request by a factor between 0 and 1. It was observed that a satisfactory outcome could be achieved by restricting the rate of traction control scaling. It also resulted in an increase in overall traction capacity. It was determined that a rate of 0.2 per second yields optimal results. The resultant traction control was also effective on snow [63].

f. Battery Model

Modelling batteries functions as the basis for battery design and control research. The two primary domains of battery modelling are the estimation of battery performance and battery design. According to studies, the number of research publications in the field of battery design is relatively low compared to battery performance, as this field is dominated by battery developers [64]. Extensive research into the efficacy of batteries has resulted in the development of a various battery types. These battery behaviour-generating models are created with the intention of simulating the performance of a vehicle. The battery models are typically categorised as equivalent circuit models or electromechanical models, though there are also analytical and empirical models available. Simulation studies involving battery behaviour and performance are best analysed using equivalent circuit models, whereas the electromechanical model is most commonly employed for battery design-related work. Due to the nonlinear effects that occur during a battery's discharge, simulating its behaviour can be difficult. In contrast to reality, battery models presume that the voltage remains constant throughout the discharge process and drops instantly to zero when the battery is completely depleted. A second assumption is that all conserved energy would be utilised and that the capacity of all discharge currents would remain constant. In practical battery systems, however, the voltage decreases steadily during a discharge, and the increase in discharge current results in a reduction in the battery's effective capacity. Table 2.2 provides a summary of common battery models used for vehicle battery performance analysis.

Table 2. 2 Summary of various battery models used in vehicles.

Type	**Commonly known models**	**Summary**
Empirical models[53]	Shepherd model Unnewehr universal model Nernst model Combined model.	Simple empirical equations are used to replicate the battery behavior. This form of models typically have a low degree of precision, limiting their applicability.They tend to operate more efficiently when both the temperature and the current are kept constant. Although their accuracy is low, they are computationally simpler because the parameters can be identified and implemented in real time with relative ease.

Electrical-circuit models(EECM)[65]	Impedance based EECMs V-I based EECMs Simple Battery Model Thevenin Battery Model DP Model	These models employ one or more electric elements to simulate the behaviour of batteries.They frequently consist of a combination of resistors, capacitors, voltage sources, and nonlinear components, such as Warburg impedance. They have a high degree of accuracy and can be used to determine all necessary battery parameters. Though considerably easier to configure than their electrochemical counterparts, EECMs still require effort, particularly when large experimental data are involved and lookup tables are required to replicate the battery's behaviour.
Analytical models[66-70]	Peukart's law Model Rakhmatov and Vrudhula model Kinetic Battery Model	These models are used to characterise the battery as a more autonomous component than those described previously. Using only a few model equations, primary battery attributes are computed. As a consequence, these models become simpler to compute than the EECMs.
Electrochemical models[71-75]	a.Shepherd's model b.Model by Jane and	The internal chemistry of the battery acts as a basis for these types of models. These models

	Morgan c. Pseudo 2D model d. Single particle model	can be used to analyse the battery's electrochemical behaviour. Design engineers must have in-depth understanding of chemical processes and parameters, and so, they are quite exact but complex in nature.

2.5. Range determination in electric vehicles

The concern that the range of electric vehicles will be diminished and they will eventually run out of fuel is an actual problem. Compared to their traditional counterparts, EVs have a longer charging time and fewer infrastructures, which makes them even less reliable. Predictive techniques for determining range must be developed that consider energy-saving aspects in addition to those based on the environment, such as road type, terrain, and weather, in order to boost the acceptance of EVs. The conventional approach to calculating an EV's range is to divide the amount of energy by the rate at which the car uses energy. However, there is a need for the creation of new models for precise range prediction in EVs due to the introduction of various car models and pervasive range anxiety. A review of the literature suggests that improved range prediction techniques are currently being developed. In 2013, Neaimeh et al. reported the creation of an accurate range prediction system for electric vehicles (EVs) that could choose the least energy-intensive route and suggested that it might increase the driving range [76]. They fed their algorithm with information on traffic patterns and the topography of the roads. The SwitchEV trial was utilised in this study to examine the energy consumption of EVs under various circumstances. Driving statistics per second for 44 EVs' were gathered over the course of two years. Over 400000 miles over the North East of England were covered in all. Then, an algorithm was modelled that assisted in reducing energy use. The Nissan LEAF, Peugeot iOn, and Smith Electric Vehicle Edison Minibus were among the EVs used in the project [76]. The data gathered at various driving speeds assisted in expanding the driving range and understanding how energy usage might result in more precise range calculations. Javier A. Oliva et al. (2013) proposed a method where precise information about the remaining driving range (RDR) helps reduce the driver's fear of having insufficient remaining range and thereby plays a part in EV acceptance. Shorter driving ranges in EVs have been identified as one of the primary factors affecting their acceptance. A model for RDR prediction using a combination of unscented filtering and Markov chains was developed in the research paper [77]. For the purpose of depicting an EV and its energy storage system, specific models were created and put into use. They wanted to use RDR to help EV drivers more effectively. The RDR was initially anticipated before being characterised for range detection. The system states and the initial battery level of charge are unknown at the start of the estimation and prediction stages. An exact initial starting point is needed in order to anticipate the RDR, the prediction module, accurately. According to Daigle et al. (2012), writers employed the unscented Kalman filter (UKF) (Julier & Uhlmann, 2004) for state estimation in nonlinear systems [78]. The trials enabled the RDR to be predicted under various driving scenarios. The outcomes demonstrated that the reported technique can reliably forecast the RDR under specified circumstances. In a different study, Zhang et al. presented an estimation method in which nine variables were considered, including the vehicle's location, remaining energy, gradient of the road, the topology of the road, vehicle velocity, driving pattern, the wind speed, the condition of any auxiliary loads inside, and the driver's driving technique [79]. The suggested methods reduced worry that the car would run out of fuel because it was computationally simple and utilised to estimate the remaining driving range. A telematics system was included in the study to gather data on the various parameters. Additionally, data from the vehicle, the driver, the map, and content providers were utilised. The Remaining Driving Distance Calculation (RDRC) was tested under three different circumstances: when the battery was empty, while there was still charge in the battery, and when the battery was fully charged. The suggested strategy has been created and put into practise in a "Smart Mobility Centre" prototype that aims to reduce driving time as well as vehicle energy consumption [79].

2.6. Conclusion

This chapter presents a detailed study on the concept of eco-routing for electric vehicles and examines the existing eco-routing navigation systems. The state-of-the-art literature associated with eco-routing navigation has been studied in detail. The fundamentals of electric vehicles, range in EVs, and range anxiety have all been discussed. It may be stated that eco-routing is widely employed in ICE vehicles; however, the concept is still in its infancy in the case of EVs. Although research is being conducted in this area, precise navigation systems are not yet commercially accessible. Prevalent systems are not easily available to common users or researchers. The expenditure of energy is a critical requirement in the construction of an optimal eco-routing system. The emphasis on energy utilisation and its minimization in EVs has been thoroughly researched. The variables that influence energy use have been found and addressed. Various academics have built and produced fuel consumption models based on the aforementioned parameters. Existing eco-routing prototypes and a few generalised models have been examined and presented. It has also been stated that a few crucial parameters, such as road gradient, are not taken into account in the majority of fuel consumption models employed. Another factor to consider while developing an eco-routing system is the battery. The elements influencing eco-routing have been discussed. According to the results of this survey, road gradient is an important influence on vehicle energy use. As a result, there is room for advancement in the development of more efficient, conveniently accessible, and compatible eco-navigation systems to aid in the improvement of electric vehicle energy efficiency.

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