Energy Consumption Analysis for the Prediction of Battery Residual Energy in Electric Vehicles

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ABSTRACT

The emergence of Electric Vehicles (EVs) is a turning point in decarbonizing the road transport sector. In spite of the various apprehensions of the customers, such as range anxiety, long charging times, higher costs, and the lack of charging infrastructures, EVs have managed to considerably penetrate into the market. Appreciable subsidies in EV purchase and possibilities of renewable energy-based local charging equipment have encouraged more and more people to own EVs. Electrifying road transport also calls for scaling up of all stages of the supply chain as it involves a lot of raw materials and critical metals used for battery technology. One of the most important factors determining the range of an EV is the energy density of the battery, which has reached over 300 Wh/kg, from 100-150 Wh/kg a decade ago. This clearly means that the same vehicle can travel double the distance with the same mass. Understanding and modeling the energy consumption in an EV is quintessential in alleviating the fear of range anxiety. This paper presents a detailed mathematical equation-based energy consumption analysis of a particular EV model for Indian roads. Very few researchers have worked on drive cycles suitable for India. The novelty of the current work is that the energy consumption calculation can be worked out for any EV model or vehicle type through simple mathematical equations.

Keywords-electric vehicle; Electric Vehicle Charging Stations (EVCSs); residual energy; aerodynamic drag; kinematics; tractive forces; rolling force;power electronics

I. INTRODUCTION

Electric Vehicles (EVs) are in the centre of attraction for researchers for quite some time. Reduced dependency from fossil fuels and lower emissions and sustainability are the key advantages of EVs. Yet, there are still few barriers to be crossed for EVs to heavily penetrate the market. These include range anxiety and the lack of charging infrastructure. Undoubtedly, EVs are going to be the future of transportation and mobility sector. Research on new materials and battery chemistries along with other innovations form the thrust for EVs to become the gamechanger in automotive sector. There are four main types of EVs, namely the Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), Plugin Battery Electric Vehicles (PHEVs), and Fuel Cell Electric Vehicle (FCEVs).

BEVs, also known as All-Electric Vehicles (AEVs) are driven using battery-powered electric drivetrain. The large battery pack which powers the vehicle can be charged by plugging into the electricity grid. The charged battery pack in turn powers one or more electric motors to run the electric car. Figure 1 shows the various components and systems in a BEV. The main components of a BEV include the electric motor, inverter, battery pack, a control module that includes the power electronic circuitry, and the transmission gear. The power for the electric motor is derived by converting the DC voltage of the battery to AC by an inverter. For acceleration, the controller adjusts the vehicle speed by changing the frequency of the AC power from the inverter to the motor. The motor then makes the wheels move with the help of the transmission system. On deceleration, the motor works as an alternator and produces regenerative power, which charges the battery.

Accurate range prediction can help alleviating the range anxiety problem in EVs. The range of an EV depends on the residual energy in the battery and the rate of energy consumption of the vehicle. There are various components of energy consumption that are related to travel (velocity, topography, inclination, etc.), weather (ambient temperature, windspeed, visibility, etc.), vehicle (auxiliary usage), traffic (congested roads), and battery (State of Charge-SoC, capacity, etc.). The battery health and degradation form an important factor determining the energy efficiency of an EV [1-9].

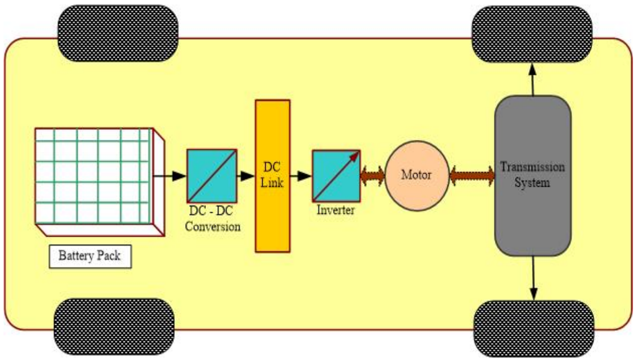

Fig. 1. Parts of an EV.

II. ENERGY ESTIMATION

Energy estimation in EVs is done with two basic approaches, namely the Forward approach (dynamic approach) and the Backward approach (quasi-static approach) [6]. The forward approach is performed using equations of the powertrain components and the dynamic interaction between them. The backward approach assumes a reference drive cycle as input and calculates the forces acting at the wheels and proceeds the analysis backward through the powertrain. Later, the model computes the motor torque and the battery energy required to power the electric motor [6].

Various energy estimation models have been implemented, including longitudinal, statistical and computer-based ones. Longitudinal vehicle dynamics-based model borrows its concepts from vehicle dynamics theory and calculates the required power at the wheels to overcome the tractive forces. Some researchers have modelled regenerative braking as a linear function of vehicle speed to estimate the energy recovered while braking or driving downhill [7]. The instantaneous EV speed and acceleration is used to provide an accurate second-by second energy consumption estimation [7]. The impact of auxiliary devices is also considered for an improved estimation. The relationship between EV power, speed, acceleration, and road grade is explored in [8] to determine the required power at the wheels. The model can be either used for instantaneous energy consumption estimation or energy consumption prediction over a trip [8]. Statistical models use real world driving data and derive empirical relationships between various factors and thus energy consumption [6]. Real-world data of EV energy consumption can be useful in building energy consumption calculation models. Considering vehicle dynamics equation as the foundation, multiple linear regression is used to construct three models. Each model uses a different level of aggregation of the input parameters, allowing predictions using different types of available input parameters. One model uses aggregated values of the kinematic parameters of trips and allows prediction with basic input parameters such as travel distance, travel time, and temperature. The second model includes detailed acceleration data. The third model uses data of the kinematic parameters as input parameters to predict energy consumption [7].

Authors in [4] used the vehicle dynamics equation to calculate the required mechanical energy and have also included added a temperature and time-dependent term to study auxiliaries and temperature-dependent efficiencies. The physical relations in the vehicle dynamics equation are used to construct three models for EV energy consumption prediction in [5]. In [6], multiple linear regression method is applied to a real-world trip and energy consumption data. The data set considers one vehicle and hence the constructed models are specific to that particular drivetrain. The influence of ambient temperature and auxiliary loads over electricity consumption is explored in [7]. An energy consumption model is proposed based on the GPS observations of 68 EVs in Aichi Prefecture, Japan. The model is calibrated through ordinary least square regression and multilevel mixed effects linear regression. The results depict that the ambient temperature directly influences the output energy losses and the interactive effects associated with vehicle auxiliary loads. Neglecting the interactive effects between ambient temperature and vehicle auxiliary loads will cause inaccurate readings of the energy consumption of the heater air conditioner [7]. Authors in [8, 9] propose a method for SoC and range estimation by considering location-dependent environmental conditions and time varying drive system losses. To validate the method, an EV was driven along a selected route and battery SoC at the destination was compared with the value predicted by the algorithm. The results show excellent accuracy in the SoC and range estimation.

Computational and statistical methods are more apt for energy estimation as they require fewer calculations than the analytical methods based on physical models. However, they are less accurate than the analytical methods. A novel methodology to estimate the driving behavior in terms of future vehicle speeds is implemented in [10]. A driving behavior model is built using a variation of Artificial Neural Networks (ANNs) called Nonlinear Auto Regressive model with eXogenous inputs (NARX). The context-aware NARX model is trained based on previous driving behavior recordings, the recent driving reactions, and route average speed retrieved from Google Maps in order to perform driver-specific and self-adaptive driving behavior modeling and long-term estimation. Authors in [1] used a vehicle kinetic model to evaluate the energy consumption in mini taxis in sub-Saharan Africa. Per-second GPS data gathered on minibus taxis include 62 trips across 3 routes with different driving conditions near Stellenbosch, South Africa. The paratransit vehicle energy consumption was estimated to range from 0.29 to 0.51kWh/km depending on the driving condition [1]. Authors in [11] proposed a method to evaluate the actual driving energy consumptions of EVs using real driving speed and charging energy information. Using energy flow analysis in the EVs, an analytic expression for estimating the energy consumption of EVs is derived. The energy consumption calculation is conducted using regression analysis. Equations for various energy split ups are also given.

The energy consumption models proposed in most of the literature are designed for specific vehicle types and specific road terrains. Most of the researchers have worked on locations outside India and the models and drive cycles selected do not match the Indian roads and climate. Automobile Research Association of India (ARAI) recommends a drive cycle that suits urban transport in India. This research work follows the Indian Drive Cycle (IDC) as its input speed profile.

Our research work focusses on building a vehicle kinematic model wherein the residual energy in the EV battery for different vehicle types and/or for varying ambient conditions can be calculated. The modified urban IDC is taken as the input speed profile in our work because its average speed and acceleration values match those on Indian roads. The energy consumption in the vehicle was calculated at regular intervals for various ambient conditions and internal parameter variations. The difference between the previous energy value and the current energy consumption gives the value of the remaining energy within the battery. The residual energy in the battery gives a clear indication about the residual range of the vehicle. Real time validation part with the help of actual data collected in the vehicle is not done. The distance travelled for a single drive cycle of IDC (10.654kms as specified by ARAI) multiplied with the number of cycles before battery charge falls below the safe margin is approximately matching the manufacturer's claim.

III. ANALYSIS OF VEHICLE DYNAMICS

An energy consumption model can be built by using forward or backward approaches. The backward approach consists of creating a vehicle model that simulates electrical parameters based on kinematic and dynamic requirements. The forward approach utilizes statistical models based on measurements of the EV consumption from real-world data or test cycles. Using real-world measurements gives more realistic values for energy consumption and relies on available data and statistical modeling [8-12]. It is mostly not associated to vehicle dynamics and drivetrain behavior. Figure 2 shows the various components in an EV and their losses.

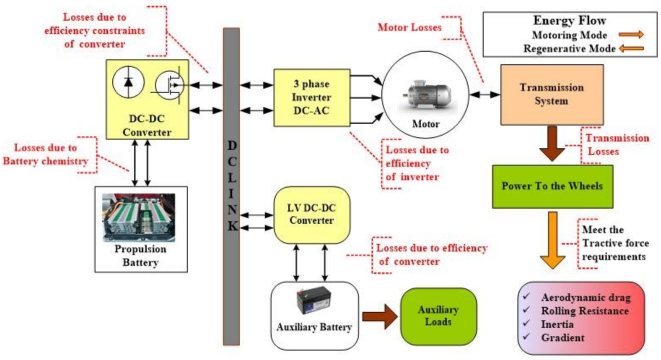

Fig. 2. Energy consuming components in an EV.

Using a vehicle model provides a direct link with the vehicle dynamics and drivetrain behavior [7-9]. Here, the influences of the drivetrain parameters on energy consumption are clearer. Though every EV has a range value specified by the manufacturer, none of the vehicles proved them. Changes that occur en-route such as wind speed, slope variations, and traffic cause mismatch in the range values due to the dynamics involved in energy consumption in real time. Authors in [9, 11] used real-world measurements for energy consumption calculation, with a limited number of external parameters are included in their models. A new approach of EV modeling that incorporates battery dynamics into motor-vehicle model and accounts for the drag force is proposed in [12]. The model is called the Integrated Battery-Electric Vehicle (IBEV) model. Two types of batteries namely lithium-ion batteries and lead-acid batteries were studied and modelled separately. The paper includes novel contributions such as EV modeling that includes the battery dynamics into the motor-vehicle model, vehicle speed and torque controller designs using LQI control, and a Kalman filter based on the proposed IBEV model, formulation of energy consumption performance indices for EV applications, and demonstrating the effectiveness of the proposed approach through a speed-control comparison study for different test cases.

From the existing literature, it is clear that there is a need for an energy model which incorporates all the important factors governing the vehicle range with an option of varying them during the trip. Including such variations can help in performing studies on real life situations that may cause the EV battery to exhaust. The current study aims to understand the energy consumption of an electric vehicle calculated from battery to wheel, thereby making it possible to predict the All Electric Range (AER). The energy consumed on real-time basis is evaluated by calculating the tractive requirements of the vehicle as well as additional power requirements included in the trip [10-18]. This primarily involves the auxiliary systems coming into play. Table I shows the details and specifications of the EV under study. The maximum battery capacity is 40.5kWh and the motor torque is 250m. The various assumptions and ambient conditions are described below.

TABLE I. SPECIFICATIONS OF THE CHOSEN EV

Parts/ parameters	Specifications
Motor	250Nm Torque
Battery	40.5kWh
Coefficients	C_{RR} = 0.02, C_d = 0.29, air density = 1.225 kg/m^3
Dimensions	Length 3993mm, width 1811mm, height 1606mm
Wheel base	2498mm
Mass	1400 kg

A. *Indian Drive Cycle*

The drive cycle selected was corresponding to the urban drive cycle or the urban IDC as suggested by ARAI. The complete drive cycle is subdivided into 2 parts. Part 1 of the IDC consists of 4 repeating cycle patterns of 195s each. Part 2 is a 400s long driving pattern with higher acceleration levels. The total distance travelled is 10.647kms [19].

B. *Analyzed Parameters*

1) *Route Slope*

The gradient of the route is one of the key factors that determine the total tractive power taken up by a vehicle. As the road grade is increased, the gradient force requirement is also increased.

2) Auxiliary Power Requirements

The AC and heating systems form an important part of the auxiliary power requirement from the battery apart from navigation, power steering and brakes.

3) Wind Speed

The effect of wind aiding /opposing the vehicle is an important energy-consuming component.

4) Mass of the Vehicle

Mass of the vehicle affects the rolling force, the gradient force, and the inertial force of the vehicle. The tractive force of a vehicle is defined as the force required to keep the vehicle in motion. The four main components of the tractive forces include aerodynamic force, rolling force, inertial force, and the gradient force.

$$F_{Tractive} = F_{aero} + F_{Roll} + F_{inertia} + F_{gradient} \quad (1)$$

where:

$$F_{gradient} = M_{Veh}\ g\sin\alpha \quad (2)$$

$$F_{Roll} = C_{RR}.\ M_{Veh}\ g\cos\alpha \quad (3)$$

$$F_{aero} = \frac{1}{2}.\ \rho\ .A_F.C_d.[(V_{Veh} - V_{Wind})]^2 \quad (4)$$

$$F_{inertia} = F_{Ia} + F_{I\varepsilon} = \delta.M_{Veh}.a \quad (5)$$

$$F_{Tractive} = (F_\theta + F_R + F_A + F_I).\frac{(1-\eta_G)}{\eta_G} \quad (6)$$

In the above equations V_{Veh} is the velocity of the vehicle, V_{Wind} is the wind-speed in km/h (positive for tailwind and negative for headwind), C_{RR}, C_d represent the coefficient of rolling resistance and the drag coefficient, respectively, g is the acceleration due to gravity (m/s^2), α is the road inclination in degrees, A_F is the vehicle frontal area (m^2), M_{Veh} is the mass of the vehicle (kg), ρ is the air density (kg/m^3), a is the vehicle acceleration in (m/s^2), and δ is the coefficient of rotary inertia.

The internal resistance of the battery is considered to be equal to 0.03725Ω. An analytical study on the various factors of energy consumption is presented in the subsequent sections.

IV. RESULTS AND ANALYSIS

An energy model suitable for a tropical country like India will require appropriate constants to be selected that can match with the weather and terrain of the place. A kinematic vehicle model should be developed in order to calculate the power consumed by the EV. In order to propose an energy consumption model, the tractive forces were calculated with the parameters of the chosen vehicle. The constants chosen are mentioned in Table I. The velocity profile was selected to be the urban IDC as recommended by ARAI [19]. Each drive cycle consists of 2 sections. The first section has 3 similar speed vs time envelopes with an average speed of 19kmph and a duration of 195s while the second section has an average speed of 59.3kmph and a duration of 400s. The second section exhibits higher velocity and acceleration values than the first one. The total distance covered per cycle is 10.647km. The calculated velocity vs time values are plotted in Figure 3. Three drive cycles are shown in the Figure.

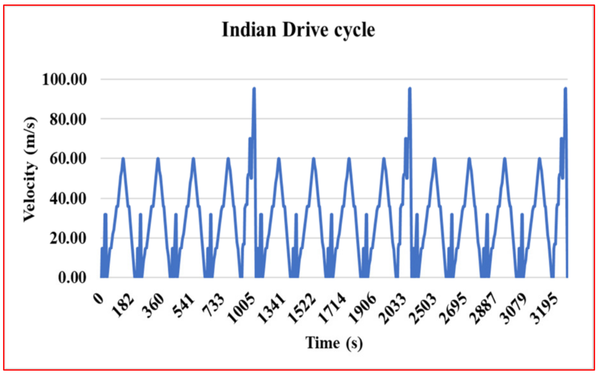

Fig. 3. Indian driving cycle.

An analytical study on various factors affecting the energy consumption in an EV was performed in Microsoft Excel and the results are given below. The internal resistance of the battery is one of the key indicators that determine the runtime of the battery. The internal resistance varies with the SoC of the battery. The internal resistance of Lithium-ion batteries goes flat from battery empty stage to almost full charge [2, 6]. The main assumption in this paper is that the internal resistance of the battery is assumed to be a constant.

A. Slope of the Road

Road gradient is defined as the rise or fall of the road level while moving along its length. In other words, it is the rate of rise or fall with respect to the horizontal distance travelled. Another way of expressing grade is that it is the percentage of rise or fall. Different types of gradients are defined, namely maximum gradient, ruling gradient, limiting gradient, and exceptional gradient [16]. The general method of representing grade is 1 in 'n' where '1' is the vertical unit and 'n' is the horizontal distance. Another common method of expressing grade is:

$$\text{Gradient} = \frac{\text{Vertical distance}}{\text{Horizontal distance}} \text{ x } 100 \quad (7)$$

Indian Road Congress (IRC) defines specific road grades for different types of road terrains (Table II [20]). The percentage value of grade is converted into degrees:

$$\text{Grade}^{\,o} = \tan^{-1}\frac{\text{Gradient (in \%)}}{100} \quad (8)$$

TABLE II. ROAD GRADES IN INDIA AS PER IRC [20]

Terrain nature	Ruling gradient	Limiting gradient	Exceptional gradient
Plain	1 in 30 (3.3%)	1 in 20 (5%)	1 in 15 (6.7%)
Mountainous	1 in 20 (5%)	1 in 16.7 (6%)	1 in 14 (7%)
Steep	1 in 16 (6%)	1 in 14.3 (7%)	1 in 12.5 (8%)

Figure 4 shows the graph of the remaining energy in an EV travelling through different road gradients of 0, 3, and 7^o, respectively.

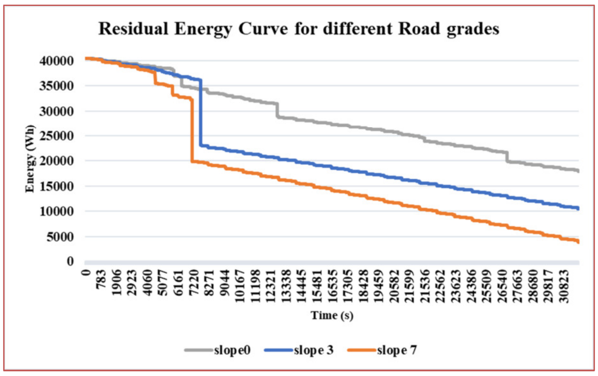

Fig. 4. Variation of the residual energy vs time for various gradients.

It is observed that the energy consumption rate increases with increase in the road gradient. The energy plot droops down linearly with increase in road gradient. Statistical analysis was conducted to determine the exact relation between road gradient and energy consumption which in turn reflects at the residual energy. Table III shows the average residual energy in the EV after running through 25 drive cycles for different road grades. Supervised statistical learning is helpful for building statistical models for prediction/estimation of an output based on one or more inputs. The residual energy values were calculated and averaged for 25 drive cycles for different road gradients and plotted.

TABLE III. RESIDUAL ENERGY VS SLOPE

Slope (°)	Average residual energy after 25 drive cycles (Wh)	Residual energy value after 25 drive cycles (Wh)
0	29062.74	18441.45
4	28464.03	16361.98
5.71	24876.73	2246.85
7	18025.33	4599.49

Figure 5 shows the variation of the residual energy values for the EV under various road slopes with all the other parameters, i.e. vehicle dimensions, air density ($1.225 kg/m^3$), C_d = 0.29, C_{rr} = 0.02, wind speed = 90mps, auxiliary load = 100W, and battery internal resistance = 0.03725Ω, remaining constant.

Fig. 5. Prediction plot of residual energy with respect to slope.

The correlation study helps establishing the relationship between two or more variables. The correlation between the two variables was analyzed using the Data Analysis tool of Microsoft Excel [21]. The predicted residual energy curve is shown in the red dotted lines of Figure 5 and satisfies:

$$y = -1561.7x^2 + 4136.9x + 26479 \tag{9}$$

The correlation matrix is shown in Table III. The value of the correlation coefficient is close to -1 (i.e. -0.8343) which means that the factors slope and residual energy have strong negetive correlation.

TABLE IV. CORRELATION MATRIX BETWEEN RESIDUAL ENERGY AND SLOPE

	Slope	**Energy**
Slope	1	
Energy	-0.8343	1

B. Auxiliary Load on the EV

Multiple factors affect energy consumption in EVs including travel-related, environment-related, and vehicle-related factors, vehicle auxiliary loads, and roadway-related and traffic-related factors [10-16]. Vehicle auxiliary loads basically serve heating, ventilation, and air conditioning purposes. The auxiliary systems in EVs are powered from an auxiliary battery which in turn draws power from the main battery. Power steering and power brakes do not have a significant impact on the vehicle range while, the air-conditioning and heating systems have a strong impact on the energy consumption, and hence range. As EVs do not have an engine producing heat to warm the car, they use battery-powered heating systems. EV batteries lose range as additional power requirements come from operating the car in cold weather. Depending on the outside temperature and the desired temperature in the vehicle, the range reduction can be significant.

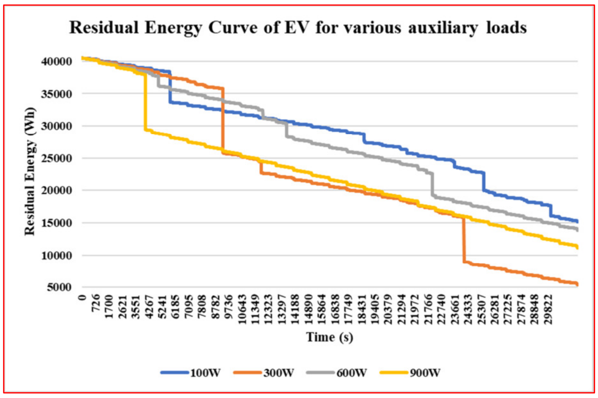

Fig. 6. Residual energy plot for increasing auxiliary loads.

Figure 6 shows the plot of remaining energy versus time for an EV connected to various amounts of auxiliary loads. The auxiliary load is increased and its influence on the energy consumption is studied. The energy calculations were done for 25 drive cycles for auxiliary loads of 100W, 300W, 600W, and 900W. It is found that the energy consumption is more for higher values of connected auxiliary loads and hence the residual energy reduces drastically as compared to lighter loads. The correlation between the two variables was analyzed with the Data Analysis tool of Microsoft Excel and is shown in Figure 7. The predicted residual energy curve is shown in red dotted lines and satisfies the fourth order polynomial equation:

$$y = -91.46x^4 + 1260.7x^3 - 5391.8x^2 + 6742.3x + 27011 \quad (10)$$

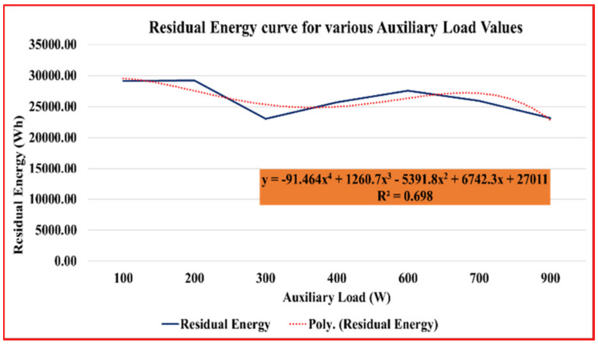

Fig. 7. Prediction plot for residual energy with respect to auxiliary loads.

The correlation matrix is shown in Table IV. The value of the correlation coefficient is -0.57 which means that the factors auxiliary load and residual energy have a weak negative correlation. The R^2 value of 0.698 was observed in the statistical study of auxiliary load versus remaining energy of the EV.

TABLE V. CORRELATION MATRIX BETWEEN RESIDUAL ENERGY AND AUXILIARY LOAD

	Aux. load	**Energy**
Aux. load	1	
Energy	-0.57	1

C. *Influence of Wind Speed*

Wind has a major impact on the range of an EV as it determines the aerodynamic drag force that needs to be overcome by the vehicle. Wind can be thought of as a vector quantity as it has a particular velocity value and its direction matters. The complexity of accounting wind speed in the energy consumption calculation is that it is very dynamic in nature, since its magnitude or direction could change rapidly. Wind increases the air resistance on the vehicle. The aerodynamic drag varies with the square of the vehicle velocity. About 70% of this drag is found to be accumulated from overall vehicle resistance at high speeds [22]. Wind direction also holds an important place in deciding the energy consumed by an EV. Winds can appear as headwinds which oppose the motion of the vehicle thus reducing its speed, or tailwinds which aid the vehicle motion. An analytical study was done on the effect of headwind and tailwind on the energy consumption of the vehicle. Figure 8 shows the variation of residual energy for different wind speeds (headwind). Vehicle dimensions, mass, drag, and rolling resistance coefficients were kept constant and the auxiliary load was fixed at 200W. The correlation between wind speed and residual energy was analyzed and the trendline generated in Microsoft Excel is shown in Figure 9. Polynomial trend-line of second degree was found to be the perfect fit for the generated curve. The R^2 value was found to be 0.9961 which shows a perfect fit. The polynomial equation is given by:

$$y = -9.8227x^2 + 66.931x + 39445 \quad (11)$$

The linear regression plot generated in Excel is shown in Figure 10. The green dots represent the actual values calculated while the blue dots represent the predicted values. The blue line connecting the blue dots shows the regression. The correlation coefficient value was found to be -0.74 indicating a negative correlation and the P value in the regression analysis was found to be 0.037 which proves that the parameter wind speed is statistically significant to the residual energy.

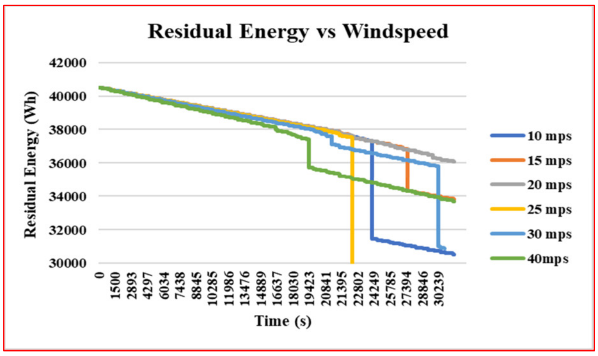

Fig. 8. Residual energy plot for various wind speeds.

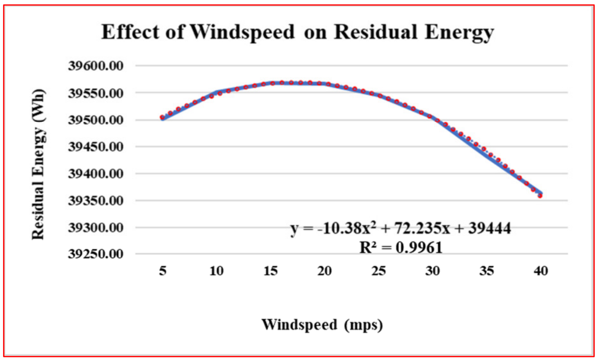

Fig. 9. Prediction plot for residual energy with respect to wind speed.

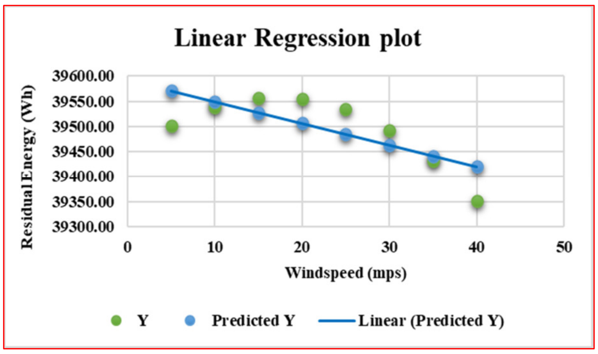

Fig. 10. Linear regression plot for residual energy vs wind speed.

D. Influence of Tire Pressure

Rolling resistance force is defined as an energy loss due to tire deformation. When the tires rotate on the road surface for a loaded vehicle, the contact area is compressed and causes tire deformation. Under unloaded condition, the tire is uncompressed and returns to original position. The deformation force on the tire under loading condition is greater than the deformation force for unloading condition. This is called hysteresis. Low tire pressure produces more hysteresis loss than high tire pressure because the tire has larger deformation. This loss is gradually reduced when the tire pressure increases [23]. Low tire pressure means low tire stiffness because the rubber molecules vibrate more than in the case of high tire pressure. The stiffness increases linearly with tire pressure [23]. Figure 11 shows the variation in the residual energy with respect to change in the rolling resistance coefficient. Differences in the road surface, especially uneven and rough roads, can result in change of rolling resistance coefficient. It is observed that a small change in Crr can cause higher energy depletion rates.

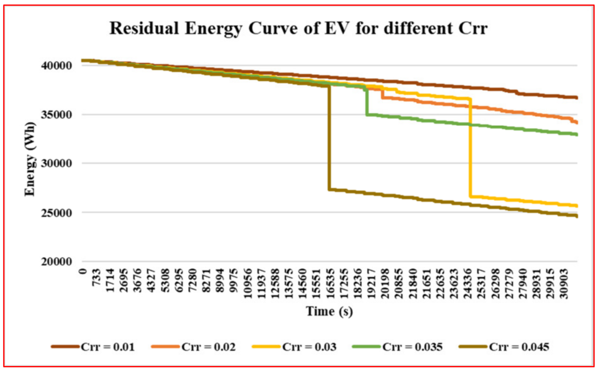

Fig. 11. Influence of road surface on residual energy.

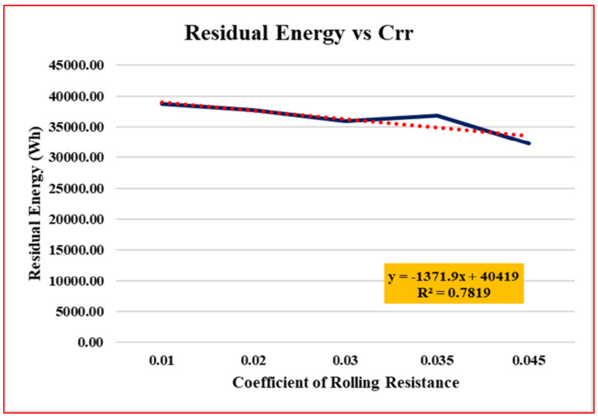

Fig. 12. Prediction plot for residual energy with respect to C_{rr}.

Figure 12 shows the results of correlation analysis on remaining energy and rolling resistance coefficient C_{rr}. The trendline is linear with the equation given by:

$$y = -1371.9x + 40419 \quad (12)$$

The R^2 value was found to be 0.7819 which shows a strong association between the parameters. The blue line in Figure 12 shows the actual values of residual energy whereas the red dotted lines indicate the linear prediction trendline which approximately falls on the points. Table IV shows the correlation matrix between the residual energy and the rolling resistance coefficient.

TABLE VI. CORRELATION MATRIX BETWEEN RESIDUAL ENERGY AND C_{RR}

	C_{RR}	Energy
C_{RR}	1	
Energy	-0.903	1

E. Impact of Vehicle Mass

The mass of the vehicle impacts directly the rolling resistance force and the gradient force. Although one specific vehicle is selected for the study, the variation in mass can be interpreted as the extra cargo that is added to it during the travel. The orange line in Figure 13 shows the actual values of residual energy whereas the red dotted lines indicate a quadratic polynomial prediction trendline which approximately falls on the points. The correlation coefficient of mass and residual energy is -0.88 which shows a strong negative correlation.

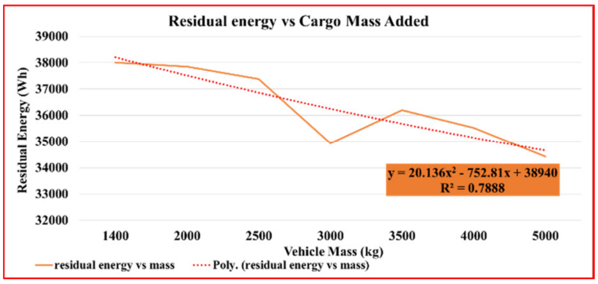

Fig. 13. Prediction plot for residual energy with respect to vehicle mass.

Modern computational tools, such as neural networks and machine learning, have been useful in studies on range detection [24-31]. The factors influencing an EV range have complex relationships and dependence over one another and hence manual calculations will not suffice. Machine learning models can be very useful in analyzing them.

V. CONCLUSION

Range anxiety is one of the biggest hurdles in the electrification of the transport sector. Accurate prediction of vehicle range and energy management methods can significantly build confidence in the minds of customers to buy EVs. The existing literature contains works on the influence of various factors governing the range of an EV. A comparison of the conducted studies shows that most researchers studied the influence of these factors considering one at a time, while the others are assumed to be constants. It is very important to know that most of the publicly available datasets are made for vehicle models outside India or for higher end vehicles. Data collected from EV fleets are mostly GPS data taken in per minute or per second form. Most studies have been conducted in countries other than India and for specific vehicle types. The transport sector in India is significantly large and diverse. The number of vehicles on the Indian roads is very large, hence demands much faster adoption of EVs compared to any other country. This work considers the Indian urban drive cycle as an input along with the parameters appropriate for Indian weather and traffic conditions. There is a need for experimental research for energy estimation and prediction in the Indian context. This research intends to build an energy consumption model for EVs that run on Indian roads. This paper presents an analytical study on the various factors affecting the energy consumption of EVs with the help of statistical methods. The factors studied include slope, auxiliary loads, wind speed, coefficient of rolling resistance, and mass of the vehicle. The Indian urban drive cycle selected for the research matches the speed profile that is possible on Indian roads. First, the tractive force required to propel the EV is calculated with appropriate constants and speed values as per the IDC and the energy consumed is calculated periodically. Five important factors were found to be statistically significant to the energy consumption of the vehicle. The level of dependence of each of these factors to the energy consumed was studied through calculations and correlation analysis. The mathematical equations for further modelling were derived from Microsoft Excel. As an extension to this work, the dependency equations can be used to build an energy consumption model that can help in the prediction of the vehicle range. This research work can result in an energy estimation model that is generic in nature and be helpful to researchers in understanding the various factors that affect the residual energy of an EV which ultimately relates to the range of the vehicle.

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