Chapter 6

Energy consumption estimation for eco-routing

6.1. Introduction

The energy predicament caused by the rising levels of air pollution in cities and the consequential global warming is causing serious implications for energy conservation and the environment at large. The automobile industry, especially gasoline powered vehicles, is reported as one of the major contributors to greenhouse emissions, which are adulterating the environment. Electric vehicles (EVs), therefore, are being considered the breakthrough technology for achieving a sustainable transport sector. It is a sector that accounts for around one-sixth of global emissions and promises to reduce oil dependence and decarbonize road transport in the future. The advantages of these systems encompass minimal to negligible carbon emissions, exceptional efficiency, reduced noise levels, and versatile operating and integration capabilities. Electric vehicles have thereby become a strong, environmentally friendly substitute for traditional vehicles. Energy usage and its minimisation are crucial aspects when EVs are concerned. It is because apprehension regarding energy shortages during a drive has been one of the greatest hindrances to the acceptance of EVs. Less consumption will result in a longer range and also improve efficiency and comfort during manoeuvres. Emphasis should be given to energy conservation schemes when it comes to electric vehicles. The concept of eco-routing in electric vehicles is a radically new approach to road navigation and opens many avenues. This technique typically uses the Global Positioning System to determine the most energy-efficient route during a trip. A comprehensive and accurate EV energy consumption model is crucial for obtaining range estimation as well as an eco-route. The primary focus of this chapter pertains to the subject of energy usage in EVs. The determinants that impact energy usage in electric vehicles (EVs) have been identified and thoroughly examined. A model for energy consumption has been developed, utilising real-time data from an electric car model to estimate the energy consumption of the vehicle. The data used in this model has been obtained from on-road test runs conducted on a lightweight neighbourhood EV prototype that has been designed and developed in the laboratory. The EV prototype has been used as a dynamic test bed to obtain data for analysis. Specified routes have been fixed, for which the energy consumption of the vehicle has been calculated. For the acquisition of data, sensors have been attached to the test vehicle, from which information on speed, acceleration, tyre pressure, road inclination, and road load has been obtained. Sensor specific acquisition and estimation techniques are required to obtain these parameters in real-time. Such methods have been applied to the test prototype for extraction of actual data from the vehicle.The energy consumption model is a physical road load model that incorporates the various factors that influence energy consumption in EVs. All data processing has been done in the MATLAB-Arduino environment. The data obtained has also been used to demonstrate that driving through an eco-route will help conserve energy, increasing the range of the vehicle. The EV is a dynamic entity whose energy evaluation is a complex and non-linear process. The energy consumption model that has been simulated considers all the major energy consumption-affecting factors, but there are still other factors that are difficult to measure or acquire. Therefore, in addition, a neural network model has also been presented that uses data from the EV prototype to predict the energy consumption of electric vehicles.

In recent years, there has been a notable increase in the prominence of electric vehicles as a more environmentally friendly and superior substitute for conventional gasoline-powered automobiles.They have come a long way from being a niche product to being one of the mainstream modes of transportation [1]. With advancements in battery technology, the development of charging infrastructure, and the growing demand from consumers, electric vehicles have emerged as a feasible choice for individuals worldwide. Research on EV is also being emphasised more by governments across the globe, including developing countries [2]. The electric vehicle industry in India is anticipated to experience substantial expansion in the forthcoming years. The nation is in a favourable position to shift towards a more sustainable and environmentally conscious form of transportation due to the presence of supportive government laws, increasing consumer awareness, and improvements in technology [3].Owing to their zero carbon footprints, EVs seem to be a boon to the environment. Despite the recent surge in sales, the analysis and development of electric vehicle technology remains incomplete, mostly due to its relatively young emergence in the market. The prevalent use of these technologies in the industry continues to pose challenges, mostly pertaining to their elevated cost, limited range, and substantial energy consumption. Research is now being conducted on several issues related to electric vehicle powertrain optimisations, routing, modelling, and path planning. There exists a strong correlation between the range and energy efficiency of EVs. Range is the distance an EV will travel, which depends on the energy it will consume during that particular trip. Lower energy consumption leads to a higher range for the EV. As fossil fuels are still used for the production of EVs, the energy involved is not purely clean. The use of energy and its conservation is a viable challenge where the concept of eco-routing navigation systems can be effectively used. The estimation of energy usage in EVs is therefore an important aspect that needs research. It can be evaluated using efficient energy consumption models. These models can be further used for the detection of range and to obtain eco-routes when developing eco-routing systems. Efficient range estimation will help in mitigating range anxiety, prevalent amongst EV users [4]. Published research shows that most navigational systems are distance-based and might not be competent to analyse energy usage effectively. There are numerous other factors that have an impact on an EV in motion and significantly increase its energy consumption. Vehicle speed, driving cycle, mass, and tyres all play pivotal roles in the usage of energy. The type and texture of the road, as well as driving habits have a significant impact on its energy use. In addition, driving on a highway produces distinct outcomes from driving in cities. Highway driving entails travelling at a high rate of speed. In contrast, city driving necessitates greater idling and frequent pauses because of traffic. These situations illustrate that the driving pattern of EVs is also an important factor. Road inclination is another factor influencing energy consumption in EVs. The grade of the road is still not taken into account by most research studies when calculating energy consumption or effective range. The EV power requirements increase with the weight of the vehicle. Consequently, factors like passenger weight and baggage weight must also be taken into account. Miri et al. presented a case study on energy consumption modelling and estimation in 2020, wherein powertrain and longitudinal vehicle dynamics were considered [4]. They developed a computer based model for the calculation of energy and tested it using a BMW i3 model on various driving cycles. Another work was published in 2019, where the researchers designed a framework based on traffic and data obtained from fellow Information and Communication Technology (ICT) devices. The framework used a hybrid system of models to filter, integrate, and convert Floating Cara Data (FDC) into traffic estimates for effective calibration of the model [5]. Zhang et al. reported a study on energy consumption using real driving condition data. Their model was based on factors like speed, acceleration, and battery State-of-Charge [6]. This mainly focuses assess the calculation of energy consumption in electric vehicles, with a specific emphasis on its application in eco-routing navigation. The implementation of eco-routing in electric vehicles (EVs) is founded upon the principle of minimising energy use. The proposed technique is a vehicle navigation system that provides the driver with guidance on the best energy-efficient route to their intended destination. Research indicates that this particular method significantly contributes to the conservation of energy in comparison to conventional gasoline-powered alternatives. It is predicated on the idea that greater travel time can be exchanged for lower consumption [7]. This theory can also be considered multiobjective because certain elements of the eco-routing navigation system tend to contradict each other. Optimisation of those factors will improve the system and produce better outcomes. It is seen that focusing on speed criteria may result in longer trip times or a lower level of battery charge. In addition, a shorter route with a higher inclination will consume more energy than a flat but longer road. An optimum solution in real-time can be accomplished by managing the EV's velocity as well as selecting a route with geometry that consumes less energy while traversing. Energy consumption has been measured and reported in many works, as mentioned above, through various methods, but it always uses a specific driving cycle and defined road conditions. Our research is focused on the energy estimation of lightweight neighbourhood electric vehicles on Indian road conditions. It quantifies the energy an EV needs during a manoeuvre and primarily emphasises on finding an eco-route for the trip so that the journey is energy efficient. Energy estimation is based on a variety of factors. This work highlights the effect of road grade apart from other involved factors. Road grade is neglected in most energy consumption models but is seen to adversely affect energy consumption. Even a slight change in inclination increases consumption manifold. The energy is estimated using a road load model on a Delhi bus driving cycle on a specific route. An eco-route has also been demonstrated, which is one of the best solutions that can be offered to improve the energy efficiency and range of electric vehicles.

6.2. Energy consumption in electric vehicles

One of the most crucial issues in designing an optimal eco-routing navigation system is undoubtedly its energy usage estimation. Only about 20% of the total energy used by internal combustion (IC) engines is used to move the vehicle [8]. EVs can operate at above 80% efficiency, lowering energy consumption. Energy usage is directly or indirectly related to a variety of elements, such as stochastic factors, meteorological conditions, and road information [9]. It has been studied that traditional vehicle fuel consumption models have overlooked changes in road elevation, which play a significant influence in energy consumption analyses. Several works have been published that contribute to the development of an effective eco-routing navigation system, consequently improving the EV range and its energy efficiency. Detection and estimation of the range of EVs usually incorporate an energy consumption model, which is the first step towards developing an efficient eco-routing system. A road load model, a battery model, a powertrain loss model, and a regenerative braking model from the vehicle wheel to the battery are general model types included in the simulation and development of energy consumption models [10]. There are various factors that affect the energy consumption of EVs. Identification of those factors and including them in the energy consumption model will facilitate better and improved results.

6.2.1. Major contributing factors

Electric vehicles energy consumption and range are affected by a number of factors. EVs, like other automobiles, suffer from reduced efficiency in certain conditions. The range of EVs can be efficiently improved by the use of simple energy and cost effective models. The energy consumption of electric vehicles (EVs) is influenced by a range of factors, which can be summarised as follows:

a. Vehicle speed
b. Vehicle mass
c. Vehicle parameters, like, aerodynamic drag co-efficient, rolling resistance, etc.
d. Driving cycle
e. Road inclination

Higher vehicle speeds increase the energy consumption of an EV. The reason behind this is that the electric motor works more when the speed is high. An optimum speed will thereby result in better energy efficiency while driving. The energy consumption of EVs also varies depending on the road type. Vehicle dynamics will change with respect to the type and texture of the road. Also, highway driving will yield different results when compared to city driving. Driving on highways involves cruising at high speeds. In contrast, city driving involves frequent stops due to traffic and also more idling. Another factor that significantly affects driving range is tyre pressure. Tyres continuously lose a certain amount of air while in use. The range of electric vehicles (EVs) can be adversely impacted by various reasons, including energy-inefficient tyre structure, sub-optimal inflation, and other related issues [11]. Road grade or inclination is yet another small but contributing factor when efficiency calculations are concerned. It has been studied that most models involving energy estimation ignore the factor of road grade in their calculations. This work demonstrates that the inclusion of road grade results in major changes in energy efficiency. The energy consumption and driving range of electric vehicles are notably impacted by driving cycles and patterns. The weight of the EV is also a factor affecting energy usage. The greater the weight, the greater is the power and energy requirement. Thus, conditions like passenger weight and cargo weight also have to be considered while building energy consumption models. Traffic on city roads affects the energy consumption of the EV. The stop-and-go movements use and waste more energy. All these criteria influence energy consumption. In an EV, energy efficiency is also dependent on factors related to the battery, such as the battery State-of-Charge (SOC), battery temperature, and Coulombic efficiency. The temperature is influenced by the surrounding temperature and exhibits an increase throughout both the charging and discharging operations, even under normal settings of voltage and current [12]. The higher the SoC, the greater the energy efficiency of the vehicle since it can run for longer periods with the available power source. The higher the CE, the less the battery loses in each cycle, which results in a longer life of the battery and thereby a higher efficiency of the vehicle [5]. In other words, with the increase in drawn current, the coulombic efficiency of the battery will decrease. EVs have the advantage of being both more cost-effective and simpler to maintain compared to their petrol counterparts. Additionally, their operational efficiency surpasses that of traditional internal combustion engines, resulting in reduced operating costs. Literature survey highlights the fact that an EV can travel twice as much distance as an ICEV with the same fuel costs.

6.2.1.1. Vehicle speed and acceleration

Electric vehicle speed and its acceleration are two of the prime factors that affect energy consumption in an EV. The speed of the EV is directly proportional to its energy usage. The aerodynamic drag of a vehicle increases with speed, which means that the energy needed to move the vehicle forward also increases. With the increase in velocity, the current consumption increases to make the motor run faster, this in turn results in more current drawn from the battery, thus increasing the energy usage. Speed and acceleration also have a significant impact on the range of an electric automobile. The faster an EV traverses, the shorter the range becomes. In addition, a quicker acceleration will result in more energy being consumed, which will reduce the range of EVs. It has been reported that hard acceleration can reduce the vehicle range by up to 50%, whereas accelerating the EV smoothly can significantly reduce energy usage, helping to extend the range [1]. These factors are therefore very important for EV drivers when planning long distance trips or daily commutes. To attain the maximum range of an EV, it is best to drive it at a steady pace.

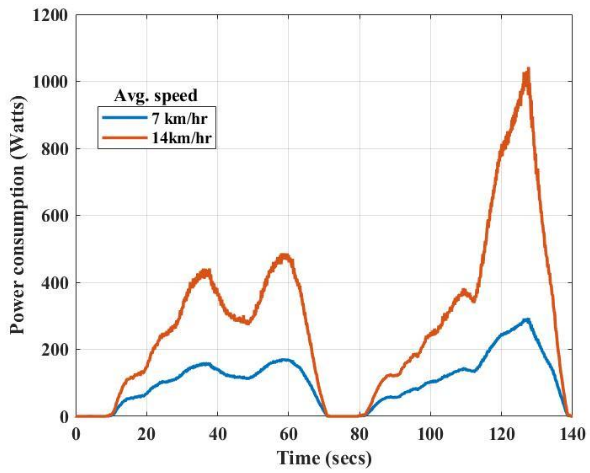

Fig.6.1 Power consumption when the EV is traversing at different average speeds.

Fig. 6.1 illustrates the power consumption along a route with different speed ranges. It can be seen that a slight change in the speed of the vehicle drastically increases its energy consumption. Therefore, as already mentioned, driving the vehicle while maintaining an optimal average speed can help in obtaining an energy efficient route and achieve better range while traversing.

6.2.1.2.Vehicle mass

Among various design features, the weight of the vehicle is a key variable that has the potential to considerably affect the energy consumption rate. Reducing the overall weight of a vehicle improves its overall efficiency. In EVs, lighter vehicles can travel farther distances, which extends the range of the vehicle and helps reduce range anxiety among drivers. A large amount of unnecessary weight can also tax the battery and diminish driving range [13]. Depending on the engine efficiency of a vehicle and the energy required by vehicle accessories, a certain amount of fuel energy is consumed to overcome forces resisting vehicle motion during a driving cycle. The relationship between energy demand and fuel consumption is not clearly addressed in the literature. Vehicle energy demand during motion depends mainly on rolling, acceleration, aerodynamic drag, and gravitational losses; and vehicle mass in particular contributes to rolling, acceleration, and gravitational losses. There are a few studies that have estimated the effect of mass on fuel consumption [14]. Biggs and Akcelik (1987) found a 10% increase in mass fuel consumption in the central business district, other urban areas, and non-urban areas by 3.4%, 4.1%, and 3.2%, respectively [15]. DeCicco and Ross (1996) estimated that a 10% reduction in the mass of a 1300 kg passenger car would reduce its fuel consumption by 6% [16]. These estimates do not reflect the partial effects of mass, where the effect is the result of a change in mass, holding all other design factors constant. The vehicle weight is hence an important criterion of consideration in energy consumption models.

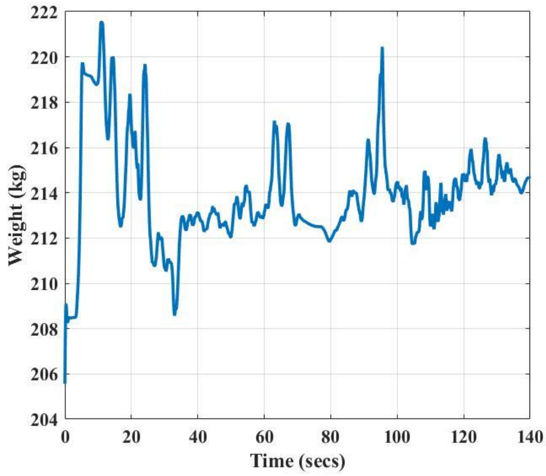

Fig.6.2 The force experienced at the wheels due to vehicle weight at various instants during a trip.

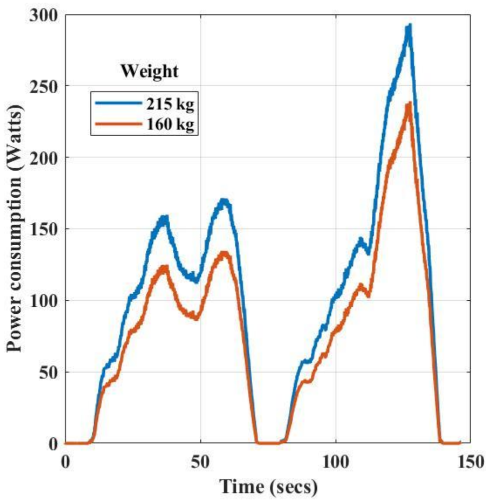

Fig.6.3 Power consumption with varying vehicle mass

The total weight of a vehicle includes its kerb weight as well as the passenger weight. Larger weights contribute more to the consumption of energy in EVs. Fig. 6.2 shows the normal force at the wheels of the test EV during a trip. The weight of the EV as a function of time can be used to estimate the force at the wheels. The force is necessary for the energy estimation as it is used for the tractive effort calculation. Fig. 6.3 illustrates the change in power consumption with varying vehicle mass. It can be clearly observed that the change in vehicle mass changes the normal force at the wheels, thereby altering the power consumption of the vehicle.

6.2.1.3. Aerodynamic drag and rolling friction

When the electric vehicle (EV) is travelling at its maximum velocity, it undergoes a state of zero acceleration. The force required to counteract this condition encompasses the aerodynamic drag force and the force resulting from rolling resistance. The aerodynamic drag force, as defined by reference [17], refers to the opposed force encountered by an item when it is in motion through the air. The significance of aerodynamics in EVs stems from their dependence on battery-powered motors, as batteries possess finite capacity and range. The enhancement of EV range and efficiency can be achieved by the reduction of drag, which effectively decreases the energy required to overcome air resistance. According to a study conducted by Tesla, enhancing the drag coefficient from 0.32 to 0.24 has been found to result in a 10% increase in the range of an electric vehicle [18]. In the context of an EV, it refers to the force that acts in the opposite direction to the vehicle's motion, thereby impeding its movement.

$$Drag_{force} = 0.5\rho_{air}\, C_{drag}\, A_{frontal}\, v^2 \tag{1}$$

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. Aerodynamic drag force tends to increase with the square of speed; thus becoming a major factor when a vehicle traverses at greater speeds. A diminished drag coefficient in an electric vehicle increases fuel efficiency, thereby improving the overall performance of the vehicle. Drag is mathematically proportional to the product of the drag coefficient, C_{drag} and the frontal area, $A_{frontal}$ of the vehicle and can be lowered by making the vehicle thinner and flatter with a frontal area as low as possible.

Rolling resistance refers to the counteracting force that is exerted on a moving object in contact with a surface. The energy necessary for the movement is not entyrely retrievable, and a portion of it is dissipated upon the release of pressure [19]. The phenomenon of rolling friction acts as a hindrance to the car's mobility, hence augmenting EV energy consumption. A rubber tyre will thus experience higher rolling resistance on a paved road than on a smoother road. Also, sand provides more resistance than a concrete floor. The rolling resistance of a vehicle has a significant impact on its motion and, hence its energy consumption [20]. The co-efficient of rolling friction can be expressed as

$$F = C_{rr} N \tag{2}$$

The rolling resistance force, denoted as F, is influenced by the coefficient of rolling resistance, denoted as C_{rr}, and the normal force, denoted as N, which acts perpendicular to the surface on which the tyre is rolling. Rolling resistance losses are attributed to the exertion of force required to counteract the friction generated by the tyres of EVs. Losses due to drag force and rolling resistance play an active role in increasing the energy demand of the EV, thereby shortening its range.

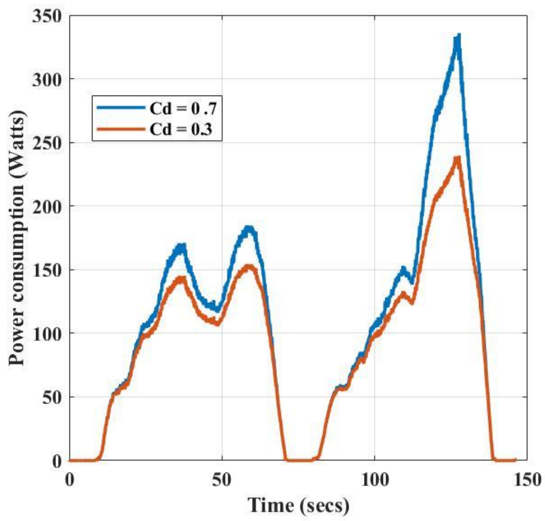

Fig.6.4 Power consumption of the test EV with varying drag co-efficients

The aerodynamic drag force causes loss that result in increased energy usage in EVs. It increases with the square of velocity therefore becoming critically important at higher speeds. Fig. 6.4 demonstrates the increase in power usage with the increase in drag. It can be seen that a slight change in the drag co-efficient results in change in power consumption. The mean consumption when C_d is 0.3 is whereas it increases 80W whereas in increases to 110 W when C_d is changed to 0.7.

6.2.1.4. Driving cycles

A driving cycle typically consists of a collection of vehicle speed data points plotted against time [21]. The purpose of this method is to evaluate the fuel consumption and emissions of pollutants from a vehicle in a standardised manner, enabling comparisons to be made between different vehicles. The driving cycle is tradionally developed using a chassis dynamometer, which allows for the collection and analysis of tailpipe emissions from the vehicle in order to evaluate emission rates.In the domain of commercial vehicles, the driving cycle is conducted on an engine dynamometer rather than a vehicle dynamometer. The evaluation of the driving cycle is based on a series of engine torque and speed points, as opposed to vehicle speed points [22].There exists two distinct categories of driving cycles: modal cycles, such as the European standard NEDC or the Japanese 10-15 Mode, and transient cycles, exemplified by the FTP-75 or Artemis cycle. The key distinction is in the observation that modal cycles consist of a combination of uninterrupted acceleration and consistent speed intervals, which do not accurately reflect actual driver behaviour. In contrast, transient cycles encompass several fluctuations in speed that are more indicative of the conditions encountered during on-road driving [23]. Driving cycles are also utilised in car simulations. In a more precise manner, these models are employed in the field of propulsion systems to forecast the operational capabilities of various components such as ICE, batteries, fuel cell systems, electric drive systems, and other similar elements [21]. The study conducted in this research involves the use of three commonly employed driving cycles for the purpose of experimentation and simulation. The three cycles under consideration are the US cycle (USDC), the European driving cycle (EUDC), and the Delhi bus drivingcycle (DBDC).

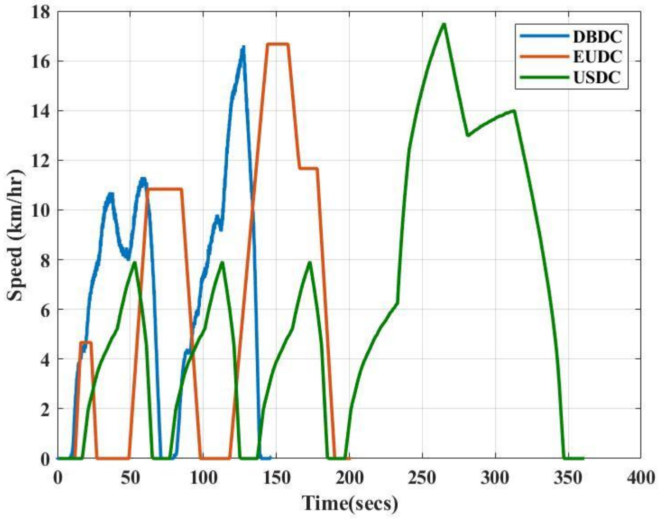

Fig.6.5 Speed profile comparison of one round of each driving cycle

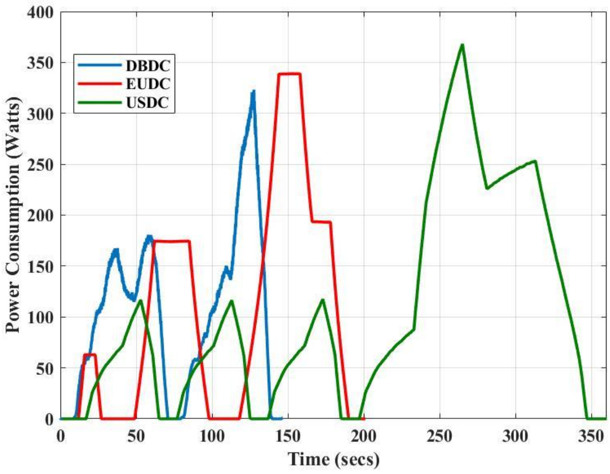

Fig.6.6 Power consumption using different driving cycles

The use of different driving cycles leads to different speed profiles thereby affecting the range of the EV. Fig. 6.5 showcases the three different cycles that have been used for experimentation. Choosing the right driving cycle is also an important criterion to consider in the design of eco-routing systems. Moreover, driving at optimal speeds results in higher energy efficiency and range for the EV.The power consumption when the driving cycles during a trip has been illustrated in Fig. 6.6. The mean power consumption along a specific trip of around 5 minutes using DBDC is 105 Watts, using EUDC is 140 watts, and using USDC is 200 Watts.These results have been obtained from the test vehicle prototype which is a lightweight bettery electric vehicle propelled by two 350W permanent magnet DC (PMDC) motors and a 24Volt, 40Ah lithium-ion battery.

6.2.1.5. Road Inclination

The gradient of a road is a significant factor that influences energy usage. The alterations in velocity and rate of change in velocity of an EV are clearly discernible. Levin et al. elucidate the impact of road elevation on the overall energy consumption of vehicles within a network [24]. The researchers have incorporated energy consumption formulae derived from road load equations, elevation data obtained from the Google API, and a dynamic traffic assignment model in order to account for the impact of user route selection. The findings of the study suggest that it is not advisable to disregard the gradient of a road when determining the path that requires the least amount of energy. The relationship between energy consumption and elevation on a road is not symmetrical or apparent. It is influenced by the average path gradient, which determines whether individual vehicle energy consumption will grow or decrease. Recent research has examined the impact of road gradient on fuel consumption and has established the imperative nature of incorporating such factors into fuel consumption models. According to existing estimates, the impact of road grade on fuel consumption in light-duty cars is anticipated to range from 1% to 3% [24]. The omission of road grade in fuel consumption models has been observed in a comparative analysis of different fuel consumption models conducted by Zhou et al. [25]. The omission of road grade in fuel consumption models can be attributed to the challenges associated with accurately estimating its impact. There exist numerous methodologies for quantifying road gradient. Historically, conventional design drawings and surveying techniques have been employed. Nevertheless, these procedures are comparatively time-consuming due to the substantial manual effort they entail. The utilisation of an accelerometer facilitates the assessment of road incline in a straightforward, precise, and efficient manner. The graphic below displays the results obtained from on-road test runs. Figure 6.7 illustrates the energy consumption associated with a journey in the absence of road gradient. Increased roadgrade values are associated with higher energy consumption, which consequently reduces the range of the electric vehicle (EV).

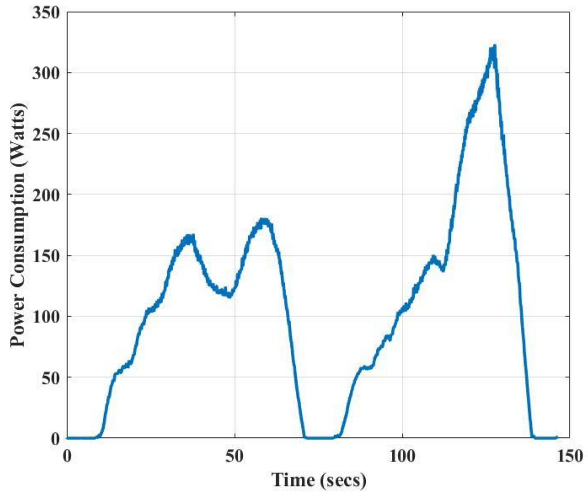

Fig.6.7 Energy consumption of EV in absence of roadgrade

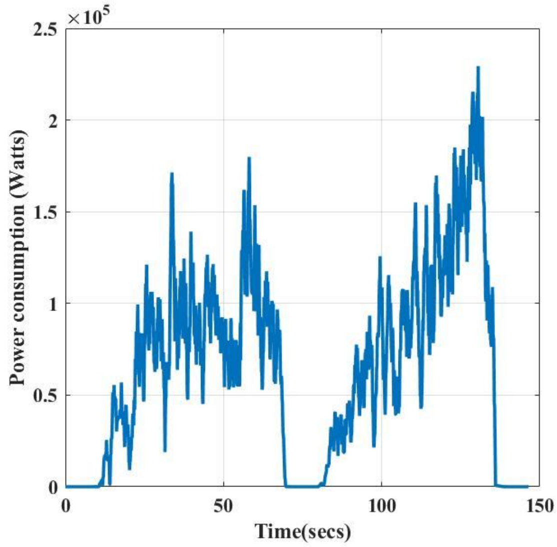

Fig.6.8 Power consumption in presence of roadgrade

The energy usage increase when roadgrade is considered has been displayed in the figure, Fig. 6.8. The impact that road inclunation has on energy efficiency can be clearly proved from the figure. Higher roadgrades cause increased energy consumption which in turn diminishes the range of the vehicle.This factor therefore cannot be neglected while developing energy efficient eco-routing systems.

6.3. Proposed design

The recent increase in pollution has renewed research in the area of electric vehicles. This rise has resulted in the development of various technological solutions and concepts in the automotive industry. A result of such concepts is eco-routing. It falls under eco-friendly intelligent transportation system (ECO-ITS) technologies, which aim at improving vehicle energy efficiency through effective vehicle navigation. Furthermore, this technology can be employed in the development of novel energy management approaches for electric propulsion systems, which aim to maximise efficiency by leveraging insights obtained from trip-specific information [26]. Less range and more energy consumption are issues acting as barriers to the acceptance of EVs. Keeping in mind these issues as well as the challenges stated above, the need for a simple, cheap, and efficient eco-routing system has been emphasised, which can be used by all EV users irrespective of the vehicle type and make. According to existing literature, a significant proportion of EV navigation systems continue to prioritise the determination of a route based on either the shortest distance or the shortest travel time between an origin and a destination. Moreover, these systems commonly incorporate other elements such as vehicle dynamics, driving patterns, road type, and traffic conditions. But a relatively lesser-known factor for calculating the energy consumption of an EV, called roadgrade is seen to be neglected in almost all cases. The determination of the most energy-efficient route for an EV in real-world scenarios is crucial for the advancement of a precise eco-routing navigation system. The system that has been proposed entails the development of a system aimed at assessing the energy consumption of electric vehicles. The system comprises an energy consumption model mainly based on road load and a dynamic electric vehicle test bed for performing on-road experimentation. The dynamic test bed is a lightweight neighbourhood battery electric vehicle (BEV) prototype that has been designed and developed in the laboratory. The details of the BEV prototype have already been discussed in detail in Chapter 3. The major parameters influencing energy consumption have been identified, and different sensors have been attached to the EV prototype for their real-time extrapolation on board the vehicle. Simulation of the energy consumption model enables estimation of the tractive effort of the vehicle. The model takes factors like vehicle dynamics, rolling resistance, and aerodynamic drag into account for its calculation. Our analysis highlights the factor of road grade, a factor that has been neglected in most fuel consumption models and not considered in any eco-routing systems. Road tests run performed on the EV allow data acquisition, which is then used for energy estimation as well as range. The eco-routing, or energy efficient route, has been demonstrated with the help of results attained from the on-road tests.

6.3.1. Extraction of parameters involved in EV energy usage

Eco-routing navigation systems mainly involve an energy consumption model for the estimation of energy consumed during a trip and also to find the most energy-efficient route during that manoeuvre. Energy estimation can prove to be of great help in improving the efficiency of the EV as well as extending its range. An energy consumption model is ideally based on various contributing factors. The model that has been presented in this work focuses on the energy affected by the road load and vehicle dynamics. The factors responsible have been identified, and various methods have been used to extract each of those parameters individually in real-time from the EV prototype. After real-time extraction of the individual parameters from the test EV, the data is then incorporated in the road-load based energy consumption model to determine the energy use of the prototype vehicle during a maneuver.Additionally, the remaining range of the vehicle has also been determined. The overall idea of the proposed system has been illustrated in Fig.6.9. Parameters are extracted from the indivual sensors and then implemented in the energy consumption model.

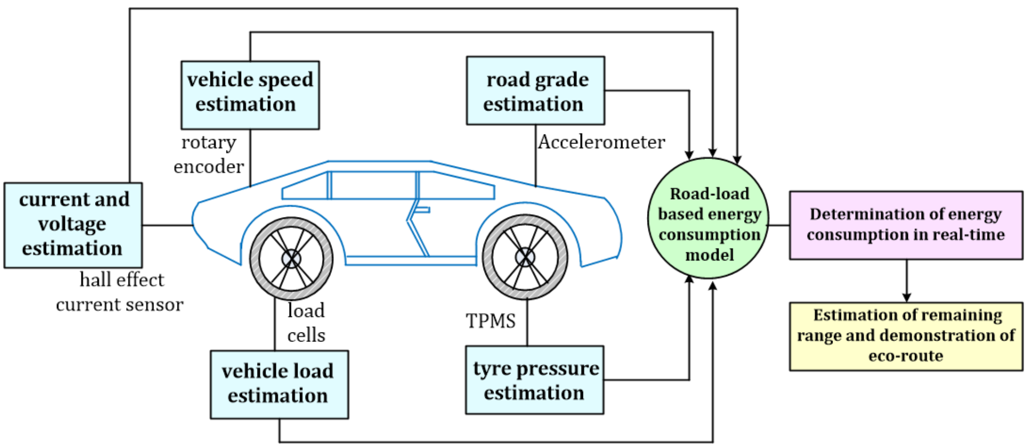

Fig.6.9 Block diagram representing working of the overall proposed system

6.3.1.1.Speed estimation

Vehicle speed is a major contributor in energy usage estimation. Increased speed and acceleration will cause increased energy consumption and a reduction in the range of the EV. For the extraction of vehicle speed, the test EV has been fitted with two incremental rotary encoders at both rear wheels. The encoders have a maximum rpm (rotations per minute) of 5000 with a resolution of 600 pulses per revolution (PPR) [27]. They have quadrature outputs for increment counting and are high-resolution optical encoders. Each encoder provides 2400 transitions between outputs A and B. It takes a quadrature decoder to turn the pulses into a count. The rotation of the wheels in the test EV causes the shaft of the rotary encoders to turn as well. The pulses are counted, and the information about the pulse rate can be used to determine the vehicle speed. The assembly of the two encoders into the prototype is shown in Fig. 6.10.

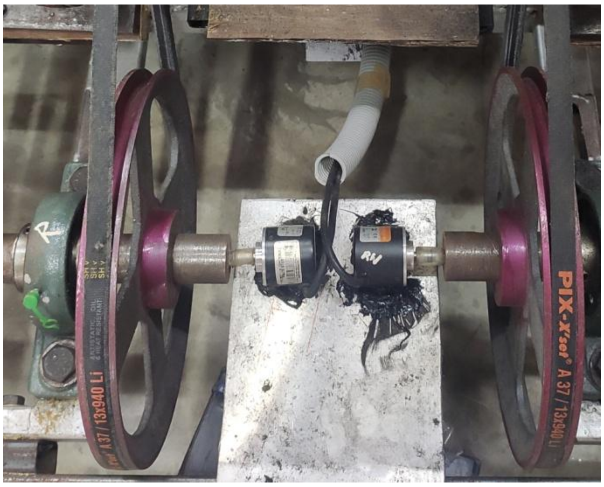

Fig.6.10 The attachment of encoders on the wheel axle of the test prototype

The vehicle speed may be precisely ascertained based on the data acquired from the encoders. The utilisation of an incremental encoder yields commendable speed and distance feedback, hence resulting in systems that are characterised by their simplicity and cost-effectiveness due to the limited number of sensors employed [27]. The functionality of an incremental encoder is restricted to the provision of change information only. Consequently, in order to determine motion, the encoder necessitates the utilisation of a reference device. The encoder delivers a predetermined quantity of pulses within a single rotation. Subsequently, the pulses can be turned into rotations per minute (rpm) and subsequently further converted into velocity. The equations pertaining to conversion are presented here.

$$rpm = \frac{encoder\ \ count * 60}{600} \tag{3}$$

Where rpm is rotations per minute, and the constant 600 is the count the encoder gives on one full rotation.

$$rps\ or\ f = \frac{rpm}{60} \tag{4}$$

The rotations per second (rps) gives the angular frequency of the vehicle and can be derived as ,

$$\omega = 2\pi f = 2\pi \times rps \tag{5}$$

The velocity or the linear displacement can be expressed as below

$$velocity = \ \omega \times radius\ of\ the\ wheel \tag{6}$$

The first step for this experiment is to determine the maximum speed and acceleration of the test EV. This has been done by test driving the protype EV. A step input has been applied in order to obtain the maximum speed and acceleration of the vehicle. This has been depicted in Fig. 6.11.

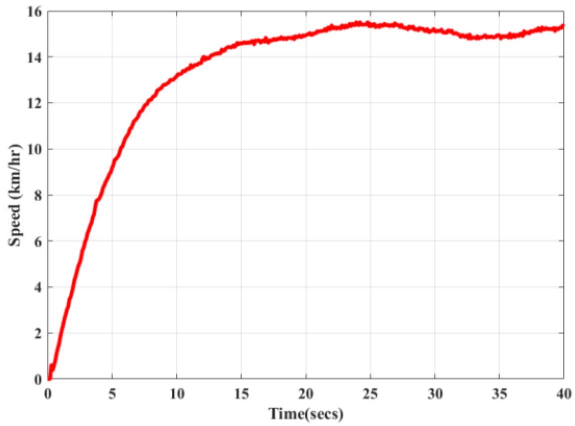

Fig.6.11 The maximum attainable speed of the test EV

On application of a step input, that is, full duty cycle is applied at the very first instant, it is seen that for a specific load, the maximum speed attained is

15 km/hr at nearly 20 seconds.The acceleration of the EV has been determined by calculating the slope at various intervals. This has been depicted in Table 6.1.

Table 6. 1 The calculated acceleration at various regions of test EV from experimental data

Slope	**First set**	**Second set**	**Third Set**	**Fourth Set**
ΔV **(m/sec)**	**3.2**	**0.5**	**0.5**	**0.4**
Δt **(secs)**	**6**	**2.8**	**2.7**	**14**
$\frac{\Delta V}{\Delta t}$ **(m/sec^2)**	**0.53**	**0.17**	**0.18**	**0.02**

The incremental rotary encoders present at the rear of the vehicle provide the velocity values of the test EV during its manoeuvre. The test vehicle has no active differential , and therefore the following assumptions have been made.

1. While traversing in a straight line, the velocity or speed calculated from both wheels is simply averaged to estimate the velocity of the test EV.
2. In the case where the EV is traversing a curved road, the speed of the vehicle at the geometric centre is derived, and then the overall velocity of the vehicle is calculated.

The overall average velocity of the test vehicle at its geometric centre can be determined with the help of the following equations (7):

$$R_L = \frac{W \times (\omega_L/\omega_R)}{(1 - \omega_L/\omega_R)} \tag{7}$$

Here, R_L is the distance of the left rear wheel from the centre of rotation.W is the trackwidth of the vehicle. ω_L and ω_R are the speed at the left and the right rear wheel respectively.The total trackwidth of the test EV is 1.03 metres.

$$R_I = \sqrt{(R_L + W_r)^2 + l_r^2} \tag{8}$$

I is the geometrical centre of rotation and that specific point has been physically determined from the test EV. R_I is the distance from the centre of rotation to the centre of the EV. W_r is the trackwidth from the vehicle centre to the left wheel and l_r is the wheelbase from the EV centre to the rear of the vehicle. The speed at the centre of the test EV can be expressed as

$$\omega_I = \frac{R_I \times W_{avg}}{R_L + W_r} \tag{9}$$

where W_{avg} is the distance from the centre of rotation to the centre of the trackwidth of the vehicle.The references for the above equations are illustrated in Fig. 6.12.

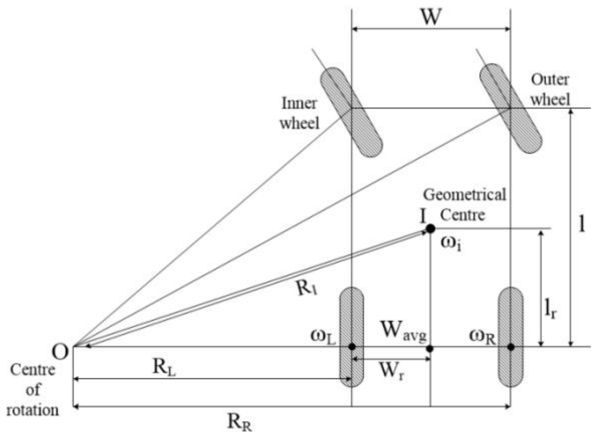

Fig.6.12 A rear wheel driven EV with its centre of rotation and geometrical centre

6.3.1.2.Load estimation

Vehicle weight is a factor that majorly affects energy consumption in EVs. The impact of weight on the use of energy has already been discussed in the previous section. An accurate calculation of the energy consumption of an EV involves the extraction of vehicle weight at various instants of time, the calculation of road load, and thereby the force on the wheels from which the tractive effort can be calculated. For the real-time acquisition of load, four load sensors have been attached to each wheel of the test EV. The kurb weight as well as the total weight when the user is driving the EV can be obtained from the sensors. They have been connected in an indirect way by using a compression spring to them, as shown in Fig. 6.13. When a force is applied to the tyre, the spring undergoes compression. The spring exerts a reactive force that subsequently compresses the load sensor, providing data on the load experienced by the wheel. Using mathematical relations and lookup tables, the actual load experienced by the wheel can be calculated. This in turn results in the derivation of force for the estimation of energy consumption.

Fig.6.13 Load sensor attached to a spring in the swing arm of the EV

A weighing scale has been used in the process of determining load in this indirect method. At first, all load cells were calibrated using known loads. The experiment for determining the relationship between the spring and the load sensor is done individually for all four wheels. At first, the weighing machine is put under one wheel without any load on the wheels. The weight is recorded. Then force is applied to the wheel, which in turn changes the weight on the weighing machine. The data is recorded and filled out in a look-up table. Then a mathematical relation is drawn by using a third-degree polynomial fitting. The load can thus be obtained. Force can be obtained by multiplying the mass with the gravitational force. The expression for force can be given as

$$F = mg \tag{10}$$

Where F is the force experienced in Newton , m is the mass of the object in kilograms and g is the acceleration due to gravity in m/sec^2. The following figure, Fig.6.14 contains the procedure of acquisition of load information experienced by a particular wheel during its maneuver.

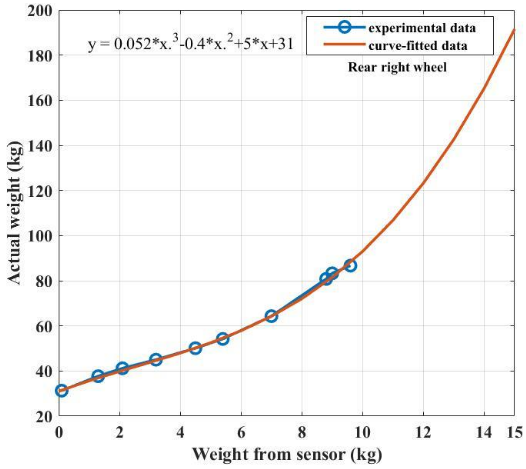

Fig.6.14 Determination of actual load by curve fitting method

The expressions for each load sensor connected to a specific wheel that have obtained by experimentally calibrating each load sensor and then curvefitting the data are expressed as follows:

$$w_{fl} = -0.25x^3 + 2.4x^2 - 0.17x + 28 \qquad \text{(front left wheel)} \qquad (11)$$

$$w_{fr} = 0.44x^3 - 4.4x^2 + 16x + 32 \qquad \text{(front right wheel)} \qquad (12)$$

$$w_{rl} = 0.28x^3 - 4x^2 + 20x + 30 \qquad \text{(rear left wheel)} \qquad (13)$$

$$w_{rr} = 0.052x^3 - 0.4x^2 + 5x + 31 \qquad \text{(rear left wheel)} \qquad (14)$$

where w is the actual load experienced by the wheel at a particular instant of time and x is the load sensed by the load sensor connected to each wheel of the test EV through compression springs. Determination of the actual load at all the wheels by this process has been shown in Fig. 6.14.

6.3.1.3.Road grade estimation

Road grade, often known as road inclination, is an essential factor that directly influences the energy consumption of electric vehicles. The process of extracting road grade in real-time involves the utilisation of a sensor known as the MPU6050, which is an inertia measuring instrument. The sensor under consideration is classified as a six-axis IMU, which implies that it provides six distinct output values. Specifically, three of these values originate from the accelerometer, while the remaining three are derived from the gyroscope[28]. The MPU 6050 is a sensor that uses micro electromechanical systems (MEMS) technology. The sensors have been used at both the front and rear axles of the wheels in the test EV. They have been placed in such a way that any crest or dip in the road can be sensed by the accelerometer. The pitch of the vehicle can be derived from the data obtained, which will in turn determine the inclination of the road. Pitch is a shift in the weight of the vehicle either forward or backward. When it happens, the weight is moving from one end of the vehicle to the other, from the back to the front, or vice versa. The accelerometer is set so that it shows a zero reading when the EV is placed on a level road. The attachment of the accelerometers to the wheels of the prototype is shown in Fig. 6.15. The expression for pitch can be given as:

$$Pitch = arctan(-a_x/sqrt(a_y^2 + a_z^2))\ radians$$

Or $$Pitch = \frac{180}{\pi} \arctan(-a_x/sqrt(a_y^2 + a_z^2))\ degrees \quad (15)$$

Fig.6.15 An accelerometer attached to one of the wheels

6.3.1.4. Tyre pressure estimation

The field of electric vehicle research has witnessed notable progress in enhancing vehicle range and somewhat alleviating the range anxiety experienced by its users. While there has been a greater focus on advancements in vehicle aerodynamics and battery technology, it is important to note that the driving range and energy consumption of electric vehicles are considerably influenced by the characteristics of the tyres [29]. Tyres experience a gradual loss of air over time. The range of EVs can be adversely impacted by many factors, such as energy-inefficient tyre structure and sub-optimal inflation. Monitoring tyre pressure in electric vehicles becomes even more critical because an EV battery weighs more than a battery used in a gas-powered vehicle. This additional weight creates increased rolling resistance because of greater friction between the road and the tyre. Rolling resistance which directly depends on tyre pressure, is critical to energy efficiency [30]. An underinflated tyre exhibits less stiffness, resulting in increased deformation. This increased deformation leads to a greater release of heat, ultimately resulting in higher rolling resistance and diminished range efficiency. Therefore, to monitor the tyre pressure while a test run is being performed on the test EV, an external tyre pressure monitoring system has been used in the vehicle. This contains four sensors that can be externally connected to the air nozzles of the tyres as illustrated in Fig. 6.16. The FR written on the sensor indicates front right wheel. Three similar sensor modules have been attached to the rest of the wheels for measurement of pressure.This system is wireless, can be easily mounted onto the test EV, and displays the tyre pressure at all times during tests to ensure that the energy consumption estimation is not affected.

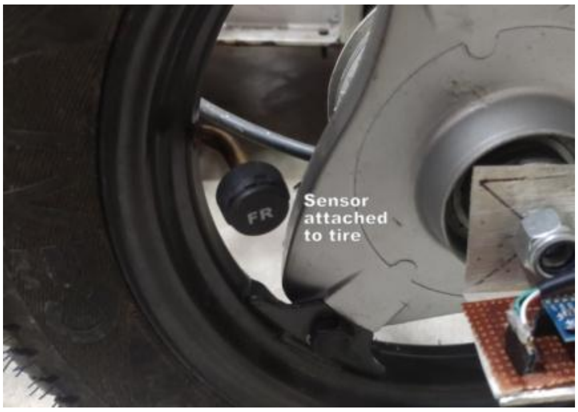

Fig.6.16 The external sensor for measurement of tyre pressure

The pressure in the tyres is seen as directly affecting energy usage in EVs. It is also a factor that is involved in the calculation of force due to rolling resistance. Rolling resistance is a function of tyre pressure and vehicle mass. The rolling resistance co-efficient changes with the change in tyre pressure as well as the type of the road on which the EV is traversing. A low pressure in the tyre will increase the rolling resistance resulting in a higher consumption of power. The significance of tyre pressure and rolling resistance on the energy efficiency of an EV has been studied in detail. The area on the road surface where the tyre meets the ground is known as the contact patch. The contact patch between surface and tyre can be used to determine the rolling resistance co-efficient and its effect on the consumption of energy. A highly inflated tyre will result in a shorter contact patch, which will lower the rolling friction and thereby the power requirement. Since the vehicle mass is also a determining factor, a heavier vehicle will create a larger contact patch, which increases the rolling resistance. It is therefore like a trade-off, and optimum tyre pressure and vehicle mass are necessary for the smooth and energy-efficient functioning of the EV. As a result of this phenomenon, the ground reaction force moves slightly forward. When the normal force acts on the centre of the wheel, this ground force creates an opposing reaction which tries to prevent the wheel from rolling. This opposing force is the rolling resistance force [20].

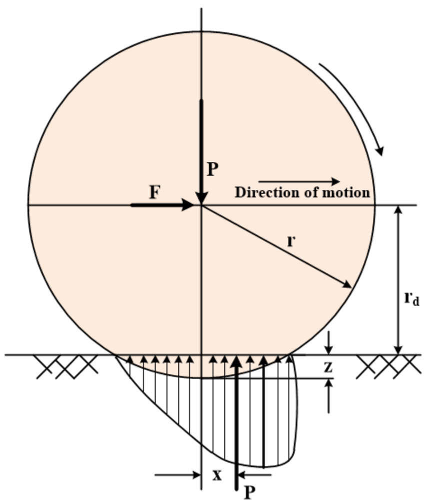

Fig.6.17 Tyre deflection and rolling resitance on a hard surface

The moment rolling resistance moment produced by the forward shift of the resultant ground reaction force can be expressed as

$$T_r = Px \tag{16}$$

where P is a force acting on its centre and a is the contact patch. The rolling motion creates a force F acting at the centre to balance the rolling resistance moment. This force is written as

$$F = \frac{T_r}{r_d} = \frac{Pa}{r_d} = Pf_r \tag{17}$$

The variable, r_d, represents the effective radius of the tyre, whereas f_r denotes the rolling resistance coefficient. The rolling resistance moment can be effectively substituted by a horizontal force exerted on the centre of the wheel in the opposing direction. The force that is equal in magnitude and opposite in direction to the force required to roll an object is commonly referred to as rolling resistance, denoted as F_r.

$$F_r = Pf_r \tag{18}$$

where P is the normal load acting on the center of the rolling wheel. For an uphill or downhill road, with a slope θ, the normal load is replaced by a component perpendicular to the road surface.

$$F_r = Pf_r cos\theta \tag{19}$$

A contact patch determination technique has been used to find the rolling resistance co-efficient for use in the energy consumption model. Two approaches were adopted. The first is a geometrical approach where the distances were measured physically and the contact patch was determined with the help of mathematical equations. The second approach is an empirical method in which the contact patch was physically measured by an ink method. The experimentation was performed at various tyre pressures by subjecting the EV to a variety of different weights.

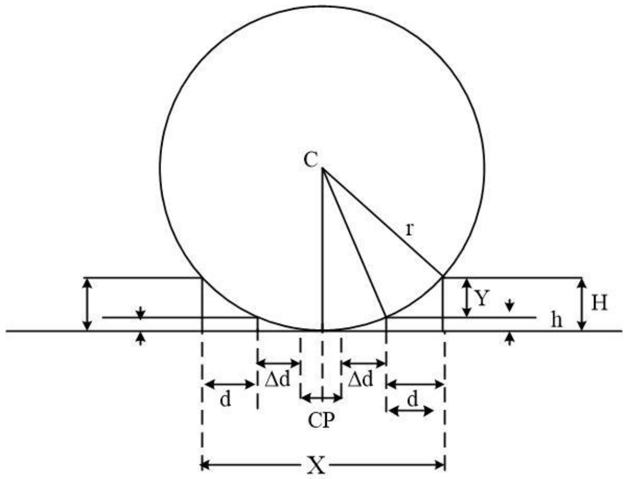

Fig.6.18 Contact patch determination by geometrical approach

In the above figure, Fig. 6.18, a geometrical approach has been adopted to find the contact patch of a tyre. Two plates of height h and H were inserted at the sides of a tyre after it is placed on the ground. The distance between each of the plates was recorded along with the effective radius r. The difference in height of the plates and the distance, X, between the thicker plates were also measured. The experiment was repeated at different tyre pressures for different weights. In the figure, Y is the difference between the plates which is 1.28mm. The distance between the thinner and the thicker plate was measured to be 1.21 cm and has been denoted as 'd'. Δd is the remaining negligible area between the contact patch and the thin plate. Here, CP is the actual contact patch made by the tyre. The mathematical derivation for the contact patch can be expressed as

$$CP = X - 2(d + \Delta d) \tag{20}$$

The second approach involves a empirical method and the actual contact patches were derived. Fig. 6.19 shows an actual contact patch at a tyre pressure of 32 psi for a vehicle weight of 60 kg, determined through the ink method. The results of both the processes were compared and it was seen that the contact patch areas achieved by both the methods are almost similar.

Fig.6.19 Contact patch physically determined by ink method (32psi, 60kg)

6.3.1.5. Current and voltage estimation

The current and voltage are two primary factors of any electrical system. They play a major role in EV energy consumption estimation too. The test EV prototype has been equipped with two separate current sensors as shown in Fig. 6.20 for recording the current consumption of both the motors. The data from the output terminal of the sensors are read into the PC interfacing them with an Atmega 328P microcontroller. The current sensors used are Hall Effect current sensors with a current range of ± 30 Amperes and a sensitivity of 66mV/A. These sensors facilitate the real-time extraction of current when the vehicle is in motion. Additionally a clamp meter has also been attached to the circuit for the measurement of current through the system. The data for the motor voltage can be obtained with the help of DC motor equations. The expression for DC motor can be mathematically written as

$$V = K_b N + I_a R_a \tag{21}$$

Where K_b is the back emf, N denoted the motor speed ,I_a represents armature current and R_a is the internal resistance of the motor armature. The motors used in the test EV are 24 Volt 350 Watt permanent magnet DC motors. The equation (21) can therefore be written as

$$24 = K_b \times 3300 + 2.5 \times R_a \tag{22}$$

$$and\ 24 = K_b \times 2750 + 19.2 \times R_a \tag{23}$$

The motors have a rated speed rating of 2750 rpm and a no load speed of 3300 rpm. The no-load current of the motor stands at around 2.5 A whereas the full load or rated current is 19.2 A. K_b and R_a can be obtained by solving the above equations from which the motor voltage can then be determined in real-time.

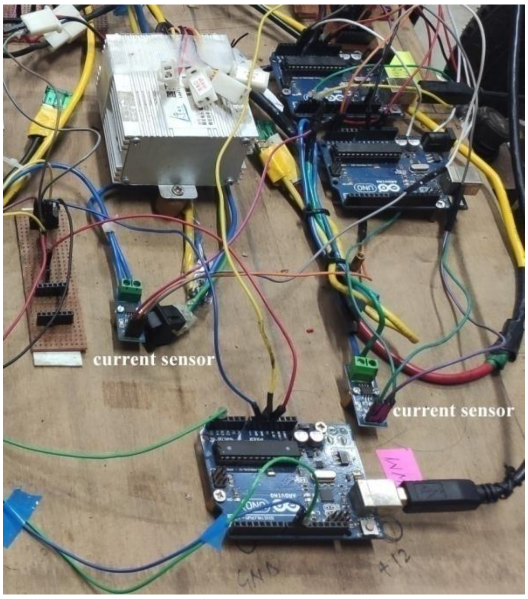

Fig.6.20 The attachment of current sensors on the test EV

6.4. Setting the driving cycle

In this study, three basic types of driving have been studied and analysed. They are the standard European driving cycle, the Delhi Bus driving cycle, and the US driving cycle. All three cycles have been scaled down to suit our experimentation purposes. Choosing the right driving cycle plays an important role in the development of eco-routing navigation systems. Though the use of standard driving cycles is seen as quite low in practice, a driving cycle is a good choice for testing or on-road experiments with the EV. A drive cycle serves as an input to the motor driving system of the EV. Therefore, it is to be ensured that the driving cycle data is in accordance with the speed and acceleration of the test EV. For experimental purposes, the Delhi Bus driving cycle (DBDC) has been chosen [31]. The original driving cycle has been plotted in Fig. 6.21. This cycle was selected because it was best suited for the purpose of our experimentation. The cycle has been scaled down by a factor of 3.2 for performing the on-road tests. On doing so, it can be seen from Fig. 6.22 that the highest speed has been scaled down to 15km/hr. This specific driving cycle has been chosen because the test EV is a lightweight vehicle and the maximum speed attainable is also low.

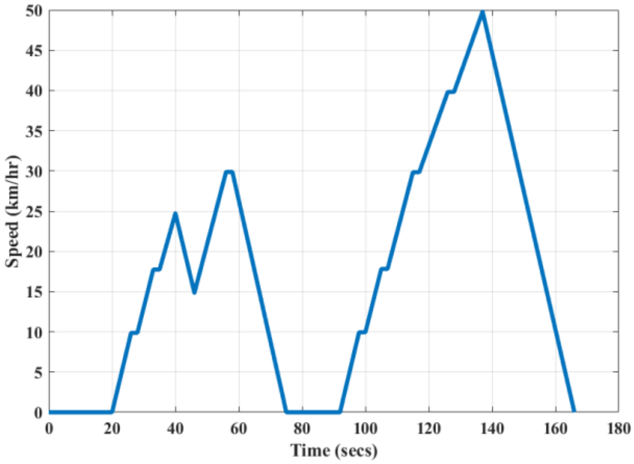

Fig.6.21 The Delhi bus driving cycle

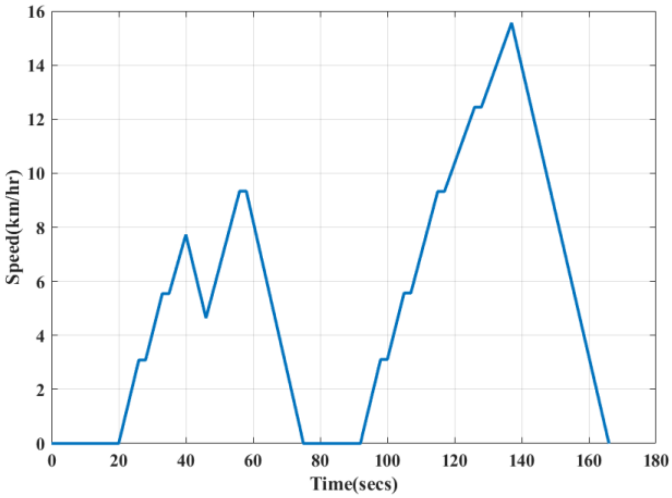

Fig.6.22 The driving cycle scaled down to fit Test EV statistics

6.5. Energy consumption estimation model

A simulation and analysis of an energy consumption model has been conducted in order to determine the amount of energy consumed by an electric vehicle during a journey. The inclusion of energy usage data is an essential requirement for the determination of an environmentally-friendly route within an eco-routing navigation system. The model utilised in this study is a physical parameter-based approach that enables the calculation of the tractive effort exerted by the vehicle on each individual wheel. The total tractive effort is the force required by EV to overcome the resistance at its wheels and move forward. The major energy usage influencing factors that have been identified have all been used in this model. This model has been tested using actual information gathered from on-road tests of the test EV prototype. In an EV, energy consumption refers to the process of calculating the total power output at the battery terminals through integration. Alternatively, it can be defined as the quantity of power utilised per unit distance or per unit time. The rules governing vehicle dynamics are universally applicable to all types of automobiles, regardless of their power sources. The equations representing the total forces exerted on a mobile vehicle [2] are as follows:

$$F_{total} = \sum(F_r, F_{grade}, F_{drag}, F_a) \tag{24}$$

Here, F_r is the rolling resistance force, F_g represents the road grade related force, F_d is the aerodynamic drag force and F_a indicates the acceleration force. The rolling resistance force depends on pressure and type of the tyre and the driven road surface which can be expressed by (25).

$$F_r = \mu z = \mu M g \tag{25}$$

where μ is the co-efficient of rolling resistance that varies with the wheel-road contact surface. The grade resistance force, depend entyrely on the road grade angle of the surface which can be given by (26)

$$F_{grade} = MgSin\theta \tag{26}$$

The force necessary to overcome the resistance through air is called drag-force which constitutes of aerodynamic drag force experienced by the vehicle. This force can be represented as

$$F_{drag} = \frac{1}{2}\rho_a C_d A_{frontal}\, v^2 \tag{27}$$

where ρ_a is the air mass density, C_d represents aerodynamic drag coefficient, $A_{frontal}$ indicates the frontal area of the vehicle, v is the vehicle speed .The acceleration force F_a can be expressed by (28), where M is vehicle mass, V_{max}

indicates maximum velocity and t_a represents time required achieving maximum speed of the vehicle.

$$F_a = M \, {V_{max}}/{t_a} \tag{28}$$

The average power required to move the vehicle at a specific velocity v can be calculated by using the following equation where t is the total time required to complete the trip.

$$P_{mean} = Mean\ Power = v \sum_{i=0}^{t} (F_{total})_i = v \frac{1}{t} [F_{total\ 1} + F_{total\ 2} + \cdots + F_{total\ t}] \tag{29}$$

The total energy required to drive the vehicle over a predefined road-trip can be obtained from (8), where t is the time required to complete the selected route.

$$E_{total} = tP_{mean} \tag{30}$$

The energy consumption information is then used for the detection of range and also a comparative analysis can be drawn for a trip which has more than one routes to find the most enery efficient or the eco-route. The remaining range of an EV can also be determined from the energy consumption information. It depends on the battery capacity, the current being consumed and the velocity at which the vehicle is travelling. The equation for remaining range of an EV can be written as:

$$Remaining\ range]_t = \frac{C_t}{I_t} (v_t) \tag{31}$$

The above equation can be used to find the amount of distance that the vehicle can travel during a trip. Here, the range at any instant of time,*t*, can be obtained which depends on the diminishing battery capacity at that instant as well as the current and velocity at the same instant. If the EV is assumed to be travelling while maintaining an average speed, the range of the EV will gradually decline along with the capacity of the battery.

6.6. Estimation of remaining range

Range in the context of electric vehicles refers to the maximum distance that an electric or hybrid vehicle may drive before its battery requires recharging [32]. The EV range is mostly determined by the capacity of its battery supply. In alternative terms, it can be characterised as the quantity of electrical energy that the battery has the capacity to retain. The range of a vehicle is primarily influenced by the driving cycle and driving style. Adopting a gentle driving style has the potential to increase the overall range of an electric vehicle. Additionally, there exist several other elements that contribute to the variability of the electric vehicle's range. The rate at which energy is utilised is primarily influenced by many factors that significantly impact the range. Several more aspects are associated with the manner in which the vehicle is operated, including the average speed of the EV, the strength of acceleration, the topography of the route, the prevailing weather conditions, and the number of passengers present. Opting for the utilisation of an eco-route has been identified as a highly effective strategy for enhancing the overall driving range. This will significantly contribute to mitigating the phenomenon of range anxiety experienced by EV customers. The implementation of eco-routing navigation strategies facilitates the optimisation of energy consumption throughout a journey. These strategies encompass maintaining a moderate velocity, refraining from abrupt accelerations, and optimising regenerative braking by engaging in coasting whenever feasible. The impact of vehicle mass on range has been previously acknowledged [33]. There is a positive correlation between mass and power consumption per kilometre. The process of battery charging is an additional variable that has an impact on the overall range of a system. Research findings indicate that maintaining a battery at a near or full charge level might have detrimental effects on both the total lifespan of the battery and the driving range of EVs.

Range estimation is a significant objective in the development of energy consumption models as well as eco-routing navigation systems. The prediction of EV range can be realised in practise through the application of advanced modelling and estimation techniques. The remaining range of the vehicle predicts an eco-route and also lessens the range anxiety of drivers to a great extent. There are a few basic parameters that are required for the calculation of range in electric vehicles. They are as follows :

1. Average speed of the test EV
2. Battery capacity of the power source being used
3. Average current consumed during the trip

The average speed of the test EV has been obtained based on the driving cycle used. In our experiment, we have used the Delhi bus cycle. The driving cycle has been applied manually while performing an on-road test of the vehicle. The battery capacity is usually fixed and known for a particular battery source. A 24V, 40Ah lithium-ion battery has been used for experimentation. Current sensors attached to the prototype give information on the current consumed along the trip during that specific cycle. The data has been measured in real-time and recorded. The speed of the vehicle has been obtained from encoders connected to the EV. The specifications used for the experiment are listed in Table 6.2.

Table 6. 2 Parameters for estimation of range

Parameter	**Specification**
Average speed	7 km/hr
Battery capacity	40Ampere hour
Current consumption	15.8Ampere

The ratio of battery capacity and current consumed results in the time the battery has till full discharge.The distance the EV will travel till the battery needs a recharge is the product of the speed and the time In this case, it is assumed that the average speed is maintained during the journey and all other factors are kept constant. The remaining range can be calculated by subtracting the distance travelled during a specific time from the total range of the EV. Therefore, in our experiment,

$$Time\ till\ full\ discharge = \frac{40Ah}{15.8A} = 2.531\ Hrs \tag{32}$$

$$Distance\ the\ EV\ will\ travel\ (EV\ range) = \frac{7km}{hr} * 2.531\ hrs = 17.7\ \cong 18kms \tag{33}$$

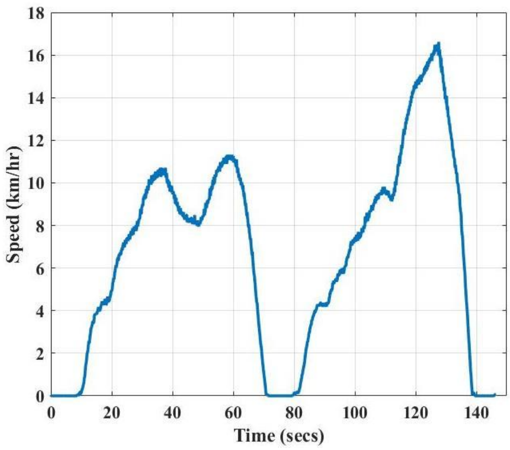

Fig.6.23 The velocity time graph of the test EV during a test run

Now, from the velocity time curve given in Fig. 6.23, we have calculated that the EV travels a distance of 270.319 metres in 146 secs at an average speed of 7km/hr. Therefore, if the EV travels a distance of 1km in 550 secs , the remaining range of the EV can be calculated as 17kms.

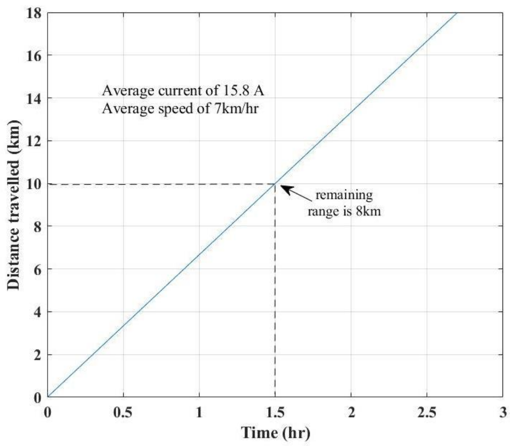

Fig.6.24 Curve showing distance travelled at a specific vehicle speed

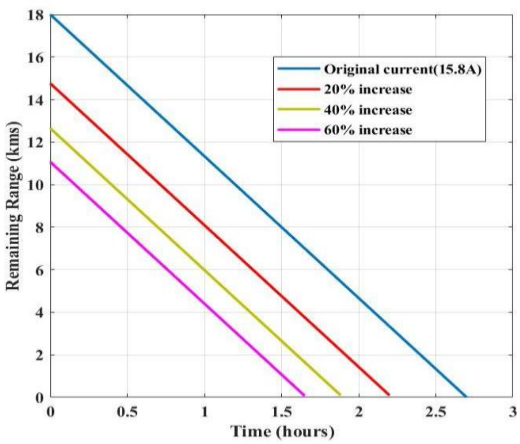

Fig.6.25 Graph showing remaining range when the current consumption increases

The figure in Fig. 6.24 illustrates the distance travelled during a specific trip when an average speed and current consumption is maintained. The increase in current consumption will result in more energy consumption thereby decreasing the total range of the vehicle. This feature has been explained in Fig. 6.25.

Alternatively, the remaining range can also be calculated from the energy consumption of the vehicle during a trip.The ratio of the distance travelled to the energy consumed is first used to determine the distance per unit energy [34]. The next step involves subtracting the total battery capacity in kwh from the energy used. The remaining range is the product of the distance travelled per unit energy and the battery energy left. Using data collected from test runs of the test EV, we have measured that at an average speed of 7km/hr and using the Delhi bus cycle, the EV travels a total of 555 meters in 300 secs. The total energy has been calculated as 0.041kwh.

Therefore, $distance\ travelled\ per\ unit\ energy = \frac{0.555\,km}{0.041\,kwh} = 13.41\,\frac{km}{kwh}$ (34)

Now, the total battery capacity in kwh can be derived as

$$kwh = \frac{Ah*V}{1000} = \frac{40*24}{1000} = 0.96kwh \qquad (35)$$

The remaining battery charge is $0.96 - 0.041 = 0.919\ kwh$. The remaining range of the vehicle can then be estimated as $13.41\,\frac{km}{kwh} * 0.919\ kwh = 12.32\ km.$ The measurement of remaining range is important as it facilitates the determination of an eco-route while development of eco-routing navigation systems.

6.7. Determination of an energy-efficient route (eco-route)

Eco-routing refers to the process of determining the optimal route for a vehicle to travel between a given origin and destination, with the objective of minimising energy consumption. This approach is proposed as a means for drivers to effectively decrease their energy usage and subsequently mitigate the environmental impact of their trips [7]. It is based on the hypothesis that extra travel time can be traded for lower energy consumption. The calibration of an eco-route helps in saving a lot of energy, which is of prime interest when electric vehicles are concerned, as well as lessening range anxiety. It assures the minimization of vehicle energy consumption as compared to traditional methods. The finding of an eco-route is based on several factors, out of which force experienced at the wheels, speed of the EV, roadgrade ,current consumption are considered major factors. An eco-route is an energy-efficient route, but it may not always be the shortest route available to reach a destination. Determining an eco-route necessitates the calculation of the energy consumption of an EV during a particular manoeuvre from a source to a destination. The energy consumption of an electric vehicle is determined by integrating the power output at the battery terminals. Alternatively, it can be defined as the quantity of power utilised per unit distance or per unit time. The rules governing vehicle dynamics are universally applicable to all types of moving autos, regardless of their respective power sources.

6.8. Prediction of energy consumption using neural network modelling

6.8.1. Basics of neural networks

The determination of range in EVs, which can lead to the elimination of range anxiety in users, is a crucial issue. Researchers are currently engaged in the investigation and development of precise range estimate algorithms in order to address this challenge. The development of a precise range estimation in EVs largely depends on the existence of a reliable power-based energy consumption model. The aim of machine learning technology has been to attempt to sort problems for which analytical models are not available. It has been modelled to achieve results where equations and laws are not promising. A neural network (NN) is one of the many technologies used in machine learning. It is a system composed of connections between nodes, which is similar to the human brain communicating through neurons. The energy consumption in EVs is a dynamic entity since there are several factors that affect the energy usage in an electric automobile during a trip. The block diagram of a general neural network model is shown in Fig. 6.26.

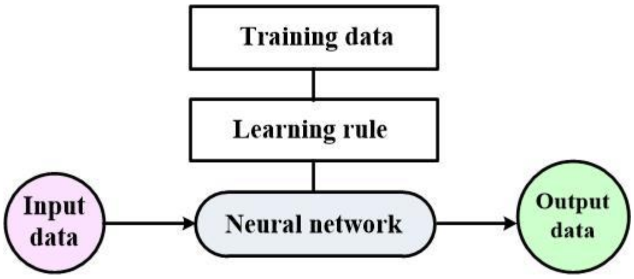

Fig.6.26 Block diagram of a generalised neural network model

A neural network model usually comprises three basic parts; an input layer, a bias layer, and an output layer. A hidden layer is present in most of the complex models, the presence of which makes the neural model a shallow multi-layer NN model. The input layer consists of nodes that transfer signals to the hidden layer and eventually to the output layer. Information about NN is stored in the form of weights and bias. The bias layer is therefore associated with the storage of information. There are various training methods that are used for modelling purposes. Training the NN with new information involves modification and adjustment of the weights. The systematic way of modifying is called the learning rule. The process also incorporates the use of an activation function. A few commonly used activation functions are the linear function, the sigmoid function, and the rectified linear unit function. The generalised equations for a neural network model are expressed below:

$$v = w_1x_1 + w_2x_2 + \cdots + w_ix_i + b \tag{36}$$

and $$y = \emptyset(v) \tag{37}$$

where w represents the weights, x is the input node , b is the bias function , y is the output and $\emptyset$ is the activation function. The most used learning rule for single layer NNs is gneralised delta rule. The expression for the generalised delta rule while using a linear activation function is as follows:

$$w_{ij} \leftarrow w_{ij} + \alpha\delta_i x_j \tag{38}$$

$$\delta_i = \emptyset'(v_i)e_i \text{ , } where\ e_i \triangleq d_i - y_i \tag{39}$$

In the above equations w_{ij} on the left hand side of the equation refers to the updated weights, w_{ij} on the right hand side of equation (37) are the previous weights , α is the learning rule which determines the rate at which the weight changes, e_i is the error of node i and x_j refers to the output from node j[j= 1,2,3,etc.]. A sigmoid activation function has been portrayed in Fig. 6.27. The updated value of weights when the generalised delta learning rule uses the first derivative of a sigmoid function is as follows:

$$w_{ij} \leftarrow w_{ij} + \alpha\delta_i x_j \tag{40}$$

$$\delta_i = \emptyset(v_i)(1 - v_i)e_i \tag{41}$$

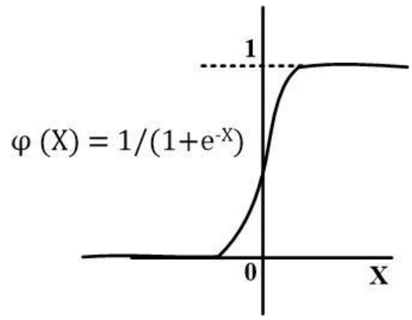

Fig.6.27 Illustration of the sigmoid activation function

6.8.2. Proposed neural network model

The neural network that has been modelled for prediction of the energy usage of an EV during a manoeuvre is a shallow multi-layer NN that consists of one hidden layer. The NN model has been illustrated in Fig. 6.28. The modelling has been carried out using nntool in a MATLAB/Simulink environment. The model has been trained with data obtained from test runs of the BEV prototype. It attempts to develop and demonstrate a neural network (NN) model for the prediction of energy consumption in electric vehicles. This NN model, however, has been developed with known inputs. The dynamic inputs can be used to make this model more robust once the energy consumption prediction is effectively done. The inputs to the system are factors that affect energy consumption in EVs. They are identified as the speed of the vehicle, mass of the vehicle, motor voltage, current consumed, and road grade. The design of the NN consists of one input layer, one hidden layer with 7 neurons, and an output layer. In Fig. 6.28, the different layers of the NN model can be clearly seen. It consists of an input layer (a_1–a_5) with a bias layer, b, a hidden layer (h_1-h_7) and an output layer. The weights introduced in the system have been marked as W_n , where n indicates the number of neurons. While it is advantageous to restrict the quantity of neurons in order to preserve the network's capacity to generalise novel information, an excessively low number of neurons might lead to a substantial impact on the deterministic characteristics of the neural network due to the initial random selection of the weighting matrix. Nevertheless, as the quantity of neurons escalates, the impact of the arbitrary assignment of initial weights diminishes on the ultimate outcome of the NN [35]. The number of neurons has been finalised based on this information. Fig. 6.29 shows the outline of the neural network that has been modelled using the nn-toolbox to predict the EV power consumption.

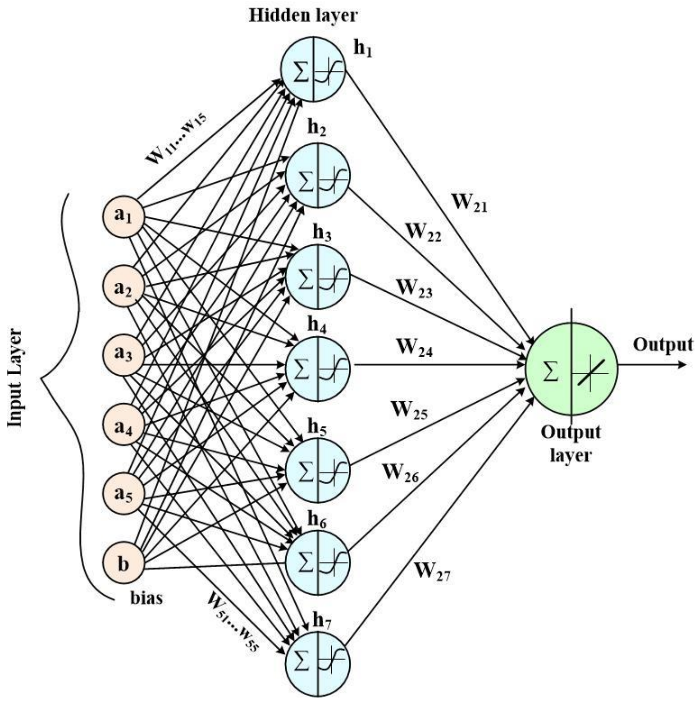

Fig.6.28 The neural network model of the system

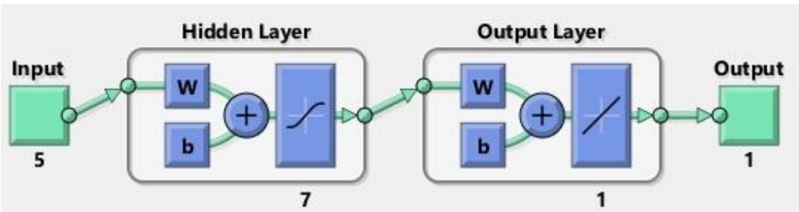

Fig.6.29 The modelled neural network using neural network toolbox in MATLAB

This model uses a supervised learning method in which the training functions update the weights and bias values in accordance with the Levenberg-Marquardt optimisation. The selection of this procedure is based on its efficiency as the fastest back propagation algorithm available, despite its reliance on memory. The backpropagation algorithm is employed to compute the Jacobian matrix, denoted as *jx*, which represents the partial derivatives of a function with respect to the weight and bias variables, denoted as *x*. The adjustment of each variable is performed in accordance with the Levenberg-Marquardt method [36].

$$jj = jx * jx \tag{42}$$

$$je = jx * e \tag{43}$$

$$dx = \frac{-(jj + I * \mu)}{je} \tag{44}$$

Where e represents all errors and *I* is the identity matrix. In the proposed model, the link between inputs, x_i, and outputs, o_k, is the Jacobian matrix do_k/dx_i. Considering our network comprises of *I* inputs, one hidden layer with *J* nodes, and one output ,*K*, [37]

$$o_k = f_2 \sum_i w_{kj} h_j \tag{45}$$

$$h_j = f_1 \sum_i w_{ij} x_i \tag{46}$$

$$\frac{\delta o_k^m}{\delta x_i^m} = \sum_j \frac{\delta o_k^m}{\delta h_j^m} * \frac{\delta h_j^m}{\delta x_i^m} = \sum_j f_1' w_{ij} * f_2' w_{kj} \tag{47}$$

The equation (45) is The gradient vector of o_k with respect to x_i . Since the NN model uses a sigmoid fuction in layer 1 and a linear function at layer 2 , f_1 is a sigmoid function, f_2 is a linear function and m is the number of observations. The model employs a gradient descent with momentum weight and bias for its adaptation learning function. The sigmoid function has been used because it can produce outputs which resembles probalities.This property makes it suitable for tasks where prediction is required such as binary problems. The weight change, *dw*, for a specific neuron is computed based on the neuron's input, *x*, and error, *e*, as well as the weight (or bias), *w*, learning rate, LR, and momentum constant, *MC*. This calculation follows the gradient descent with momentum approach. The derivation of this can be shown as follows:

$$dw = MC * dw_{prev} + (1 - MC) * LR * gW \tag{48}$$

To construct the training data set, a series of on-road tests were conducted on the experimental electric vehicle (EV) along a predetermined path. A neural network is trained to effectively establish a mapping between a given set of input variables and a corresponding set of output variables. The neural network model is trained in a suitable manner to accurately anticipate the output by considering various input signals that are applied.

6.9. Results and Discussion

Energy consumption estimation is a vital component of an eco-routing navigation system in electric vehicles. The power requirement of an EV during a manoeuvre has been estimated by using a road-load based energy consumption model. The data used for evaluation of the model is real-time practical data obtained from on-road test runs of the developed EV prototype. The test EV is a lightweight neighbourhood battery EV powered by a 24 V, 40 Ah lithium-ion battery and propelled by two 350 W PMDC motors. The EV is independent and rear-wheel driven. The data comprises the major factors that were identified to majorly influence energy efficiency and have been acquired from sensors attached to the EV. The data has been logged through a data acquisition system that consists of microcontrollers and a laptop. The obtained parameters were then used for the calculation of the energy consumption of the EV and the range of the vehicle. All results have been processed in a MATLAB-Arduino environment. The results obtained are in accordance with theoretical data as well as with the results obtained during preliminary simulations. The factors used in this model have been fairly analysed, and the results have been sub-sectioned into groups, which are discussed below.

6.9.1. Significance of driving cycle and tyre pressure on energy consumption

Driving cycle and the tyre pressure of the vehicle are factors that directly affect the consumption of energy and its efficiency in EVs. The driving cycle is a measure of speed and time and serves as an input to the motor driving system of the EV. It is therefore necessary to ensure that the driving cycle data is in accordance to the speed and acceleration of the test EV. The DSBC has been used to test the model developed, and its effect on energy usage has been studied. Fig. 6.30 shows the speed profile of the test EV when two different driving cycles, the EUDC and the

DBDC, are used. It can be observed that the use of different driving cycles leads to different speed profiles, thereby affecting the range of the EV. The drive cycles have been adjusted to match the speed and acceleration capacities of the test EV. The average speed of the DBDC here is 7km/hr and the EUDC is 5.5km/hr. The role of driving cycles in energy consumption can be clearly noted in the figure.

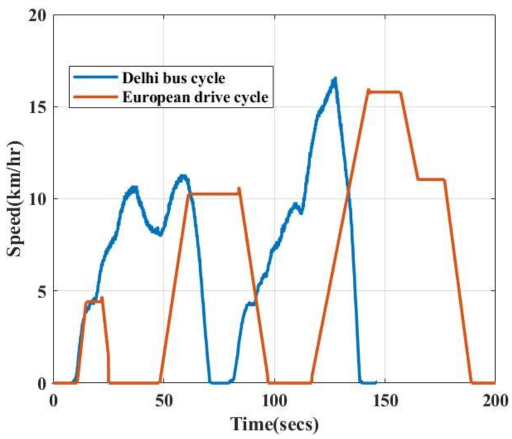

Fig.6.30 Speed profile of test EV using different driving cycles

Tyre pressure is another factor which affects energy consumption in EVs. It is also related to the vehicle weight, which varies accordingly. The significance of tyre pressure and vehicle mass has been discussed in this chapter. Rolling resistance is a function of tyre pressure and vehicle mass. The contact patch of a tyre with the surface of the ground can be used to determine the co-efficient of rolling resistance, which is a primary contributor to the force due to rolling resistance in the tractive effort calculation. Two approaches were used for the determination of the contact patch. The first method consists of a combination of an empirical and a geometrical approach, whereas the second method is a physical determination technique. Results from both methods were compared and have been presented. Fig. 6.31 depicts the area of contact at various tyre pressures. The relationship between them is linear because the increase in tyre pressure will lead to an increase in tyre inflation, which will reduce the contact patch. The reduction in the contact patch will also reduce the rolling resistance of the tyre. A curve fitting model has also been included through which the patch areas for any tyre pressure can be achieved.

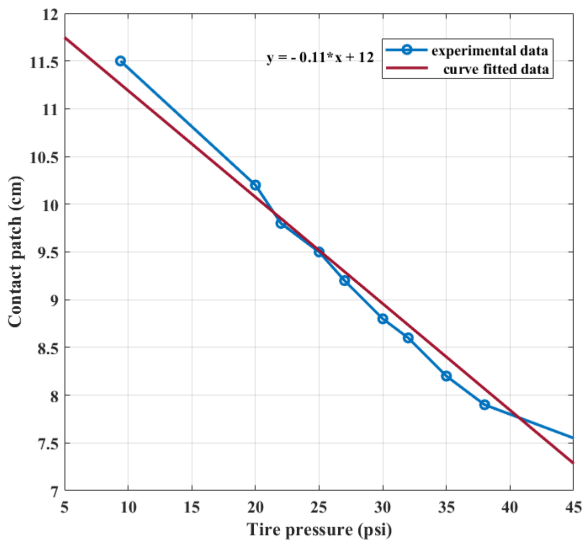

Fig.6.31 Contact patch determination using the empirical method

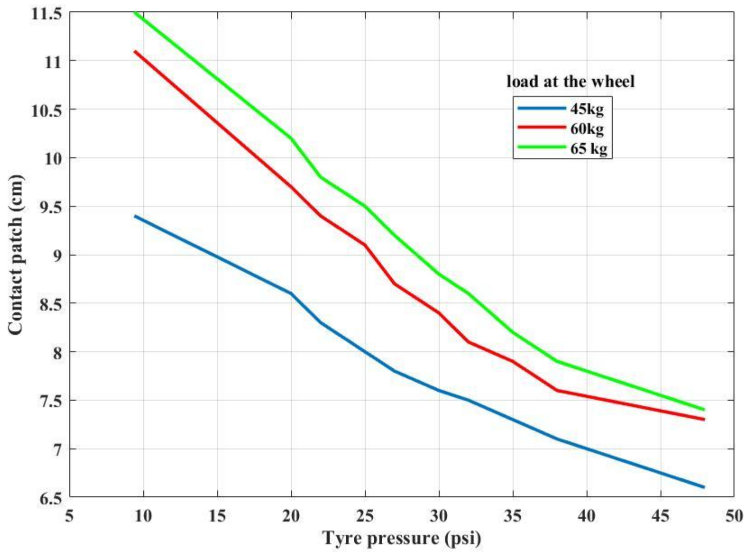

Fig.6.32 Comparison of contact patches as a function of tyre inflation and vehicle weight

The rolling resistance co-efficient is a function of weight as well as tyre pressure. A comparison of the contact patches made by a tyre at varied weights has been illustrated in Fig. 6.32. The figure clearly shows the change in the contact patch with respect to tyre pressure as well as to varying loads. The tyre subjected to experimentation has been introduced to loads in ascending order starting at 45kg. The figure shows results at three different loads of 45 kg, 60 kg, and 65kg. The change in loads at the wheel significantly changes the contact patch and thereby the rolling resistance.

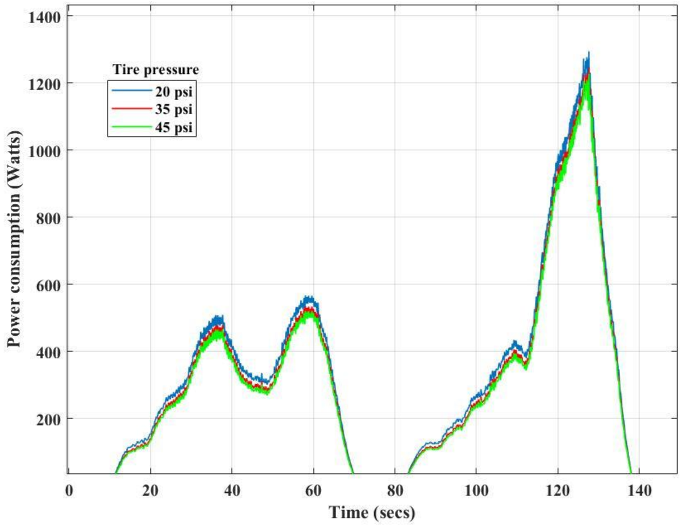

Fig.6.33 Power consumption at various tyre pressures

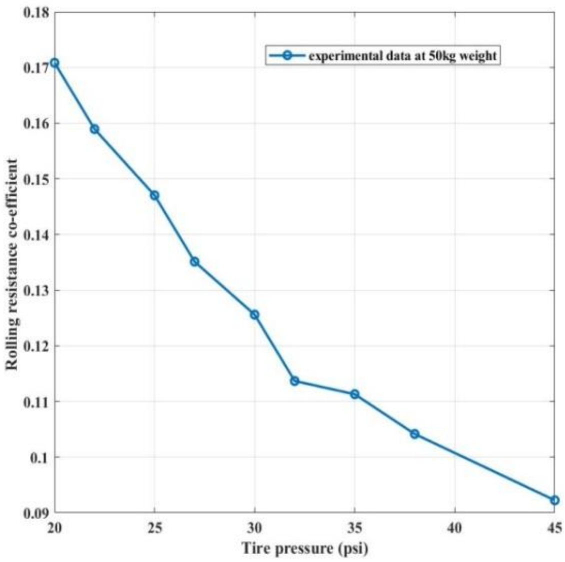

Fig.6.34 Rolling resistance coefficient as a function of tyre pressure

The use of the road load model shows that the power consumption of an EV changes with the change in tyre pressure. The factor of pressure is not directly involved in the model but indirectly affects the rolling resistance, which in turn influences the energy usage. This concept is portrayed in Fig. 6.33, which shows that the consumption increases with an increase in the pressure of the tyres. It can also be observed that the difference in consumption increases when the vehicle is accelerating which is almost neglible when it is undergoing deceleration. The rolling resistance coefficient has been determined with the help of the mathematical formulations discussed above, and the results have been plotted in Fig. 6.34. The curve illustrates the rolling resistance co-efficient as a function of tyre pressure. It can be seen that at a specific load, the increase in tyre pressure decreases the rolling resistance, which again reduces the energy consumption of the vehicle. The co-efficient can be obtained for any pressure range by using simple curve fitting tools. It is, however, necessary to note here that though the increase in tyre pressure leads to the minimisation of energy use, the pressure in tyres is usually maintained at a standard, and over or under inflation of tyres causes other complexities that ultimately lead to increased energy consumption.

6.9.2. Estimation of energy consumption using road-load model

The energy consumption model has been used to obtain various parameters related to energy usage in EVs. These parameters are essential in the analysis of efficiency during the determination of an energy-efficient path. The data used for simulation of the model is real-time data of road test of the EV prototype on a route. The route considered for road tests as obtained from Google maps, have been shown in Fig. 6.35. Fig. 6.36 illustrates the drive cycle of the test vehicle during the trip, which is the speed profile maintained during the manoeuvre. The figure depicts one cycle of the pattern. The cycle is repeated in the same pattern until the destination is reached. It can be seen that the peak speed achieved is 16km/hr. The sample time here is 100 ms. An ammeter has been connected to each motor, and the current drawn or consumed at every instant has been obtained. It is seen that an average of 15 A of current is drawn during the trip. The current profile for both motors has been shown in Fig. 6.37. The voltage across the motors can be quite easily determined from the current data obtained. The voltage has been back calculated using the voltage equation of the DC motor. The voltage across the motors has been depicted in Fig. 6.38.

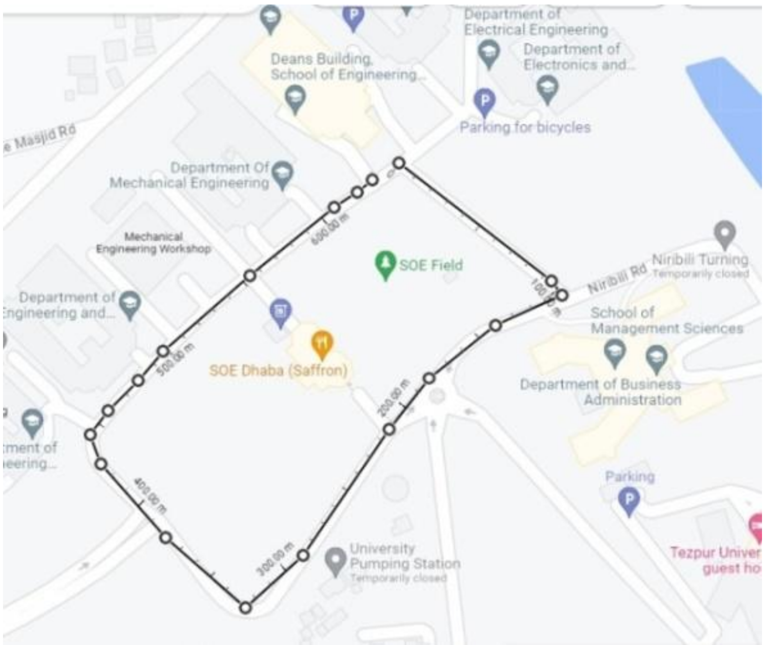

Fig.6.35 Chosen route for road test of EV prototype [38]

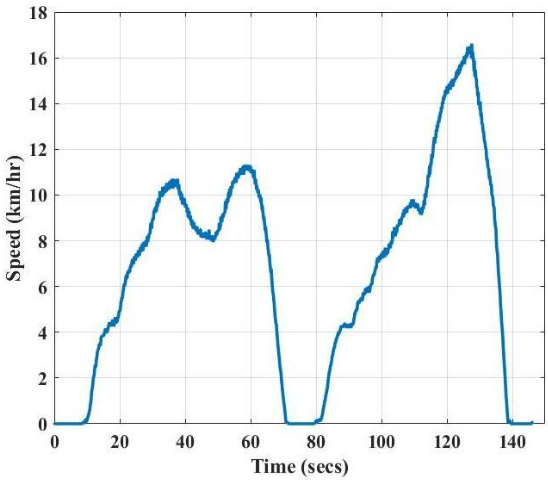

Fig.6.36 The driving cycle pattern chosen for the test EV

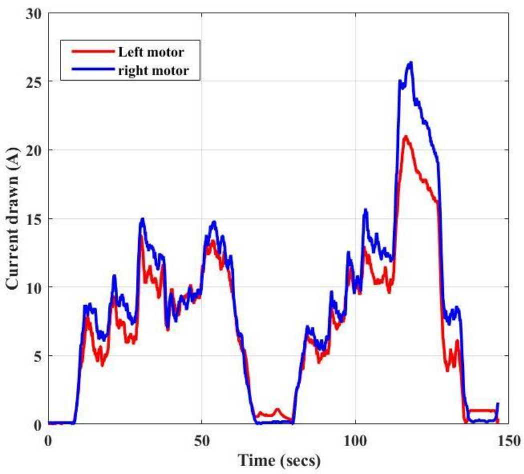

Fig.6.37 The current consumption profile during a trip

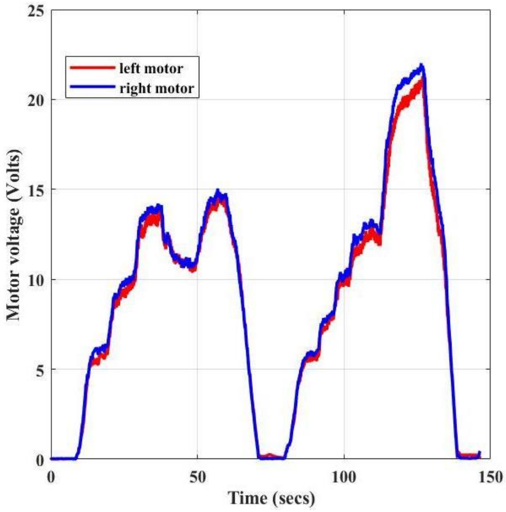

Fig.6.38 The voltage across the motors of the EV during the trip

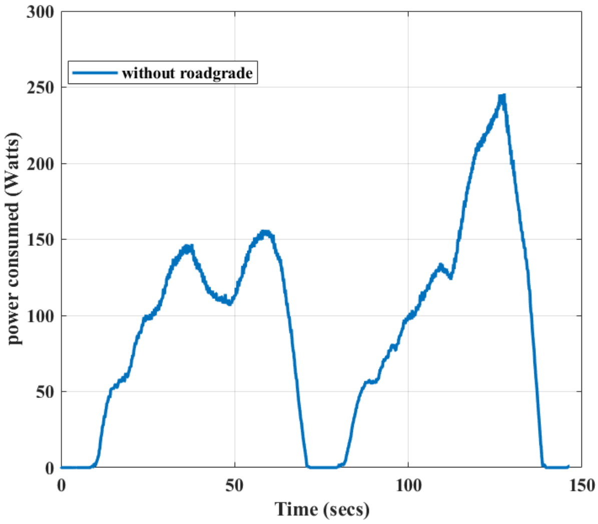

Fig.6.39 Power consumption of the test EV during a trip

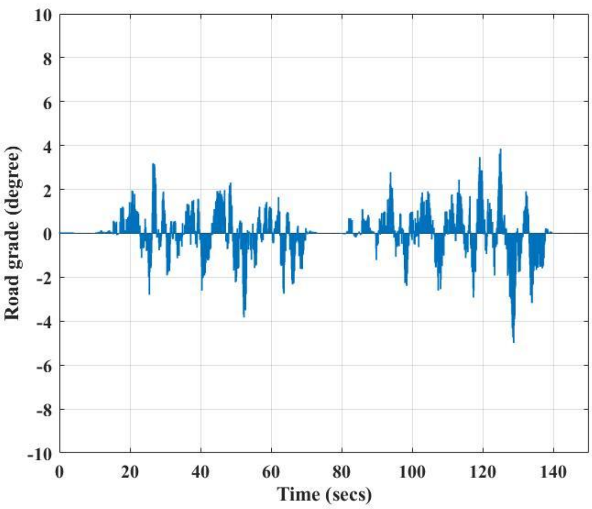

Fig.6.40 Roadgrade profile of the test patch

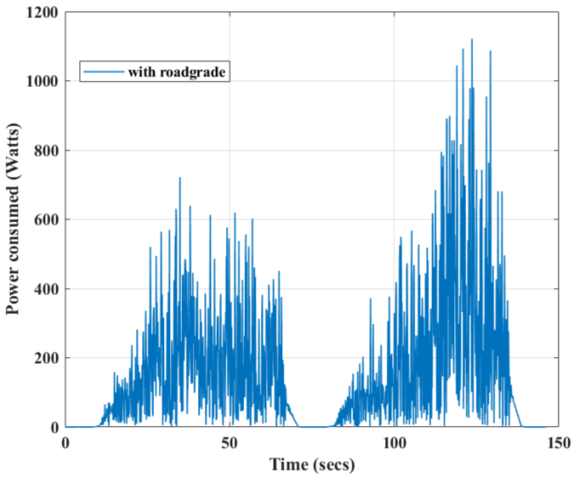

Fig.6.41 Power consumption of the test EV in presence of roadgrade

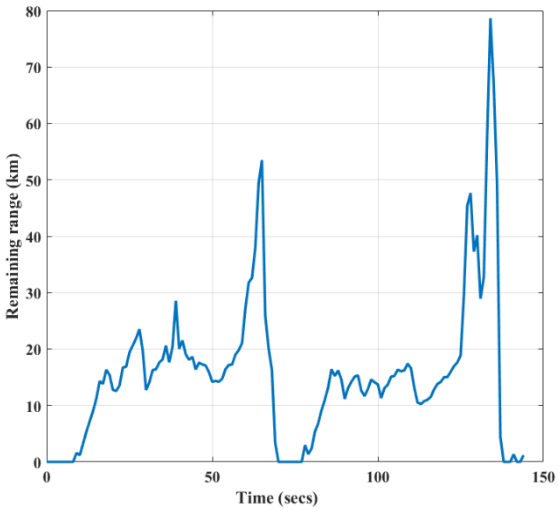

Fig.6.42 Remaining range estimation at every instant along the trip

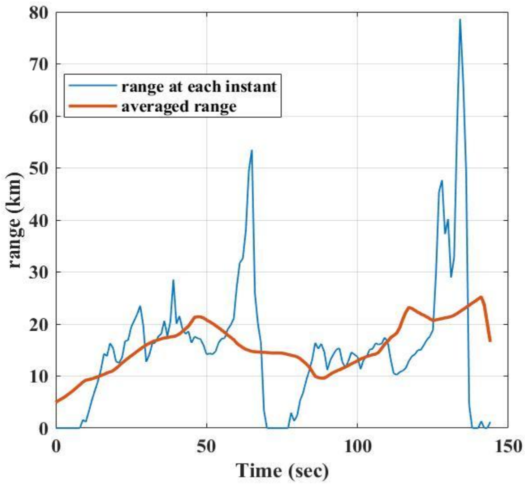

Fig.6.43 Comparison of instantaeous range estimation and averaged range

The power consumed during the trip has been estimated from the energy consumption model. Energy is mathematically the power integrated over time and so the amount of energy used can also be calculated. This model emphasises the effect of roadgrade grade, so results in the presence and absence of the road inclination have been presented here. Fig.6.39 illustrates the power consumption of the test prototype in the absence of roadgrade. It can be seen that the mean power consumption is around 90 Watts. The roadgrade profile is shown in Fig. 6.40. It can be observed that even when the road looks flat to sight, there is always some amount of grade present, which affects energy consumption in EVs. The power consumption in the presence of roadgrade along the route has been depicted in Fig. 6.41. The plot clearly highlights that the average power almost doubles to 150

Watts with only a slight introduction of grade along the traverse route. The time of travel as per the figures presented is 150 seconds, which measures the energy consumed to be 13.4 kJ in the absence of grade, which increases to 22 kJ when roadgrade is taken into consideration. The energy estimated in this process can be used to easily find an eco-route, or the route consuming the least energy. The utilisation of hall-effect current sensors integrated into the test prototype facilitates the instantaneous extraction of real-time current consumption data. In order to ensure consistency in all calculations, a sample rate of 0.1 seconds has been maintained. Figure 6.42 provides a visual representation of the residual range of the automobile during a designated manoeuvre. It is widely acknowledged that an increase in the current consumption of a battery leads to a reduction in its capacity, thereby resulting in a loss in the range of the vehicle. In this particular scenario, it is noteworthy that the temporal duration is rather brief, and the magnitude of the current, as well as the velocity, of the test EV, undergoes continuous fluctuations every instant. Hence, it can be observed that the range varies continuously, resembling the driving cycle pattern, ultimately resulting in a reduction of the vehicle's range. The test prototype uses a 40Ah lithium ion battery and when it is driven using the Delhi bus driving cycle it is observed to maintain an average speed of 7kms/hr as shown in Fig.6.36. The current consumption data states that the average usage is around 15 A. This data thereby gives us a remaining range of around 15kms if the EV is driven under similar road conditions. The data presented in Fig.6.42 shows that the range constantly varies with time. Although the range may seem to peak or decrease at a specific instants due to various factors, it can be observed in Fig.6.43, where the range have been continuously averaged, that the test EV possesses an average remaining range of around 15 kilometres at the start of the journey which will decrease as the EV moves towards its destination.

6.9.3. Demonstration of an eco-route

Eco-routing systems aim to identify the route that maximises energy efficiency in scenarios when multiple options exist for reaching a given destination. The reduction in energy consumption serves to alleviate concerns regarding range anxiety, while simultaneously increasing the overall driving range of the electric vehicle (EV). This analysis presents five different situations to illustrate the concept of an energy-efficient route, sometimes referred to as an eco-route, for a trip. In the first scenario, depicted in Figure 6.44, two routes of equal distance have been evaluated for the purpose of travelling from Source A to destination B.The driving cycle utilised for all scenarios under consideration is the Delhi bus driving cycle. Case 2 pertains to a case wherein there exist two distinct routes connecting a common origin and destination, with variation in their respective lengths. The third scenario examines two comparable routes with varying lengths and distinct weather conditions. The short pathway exhibits dry conditions, resulting in increased rolling resistance for the tyres. In contrast, the lengthier route exhibits wet conditions, resulting in reduced resistance at the tyre surface. Case 4 exemplifies a scenario in which an eco-route is identified, whereby two distinct routes of varying lengths are available, and the shorter route exhibits a larger traffic ratio. Case 5 demonstrates the influence of crosswinds and aerodynamic drag on the eco-routing navigation of electric vehicles (EVs). In this case, we are examining two routes of equal distances, where one of the routes is subject to the influence of crosswinds.

i. Case 1 :

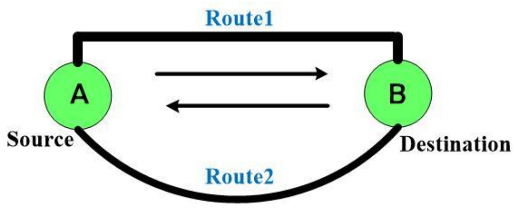

Fig.6.44 Illustration of two routes of same length from source A to destination B

The test EV is maneuvered from source A to destination B along the two routes, Route 1 as well as Route 2. It has already been mentioned that the two routes are of the approximately the same length. This means that while driving at the same speed using the same driving cycle, it takes almost the same time to reach from A to B. In such a case, the EV user will face a dilemma as to which road to use to take the trip. The calculation of the total energy consumption during the trip can help to find the more energy efficient route out of the options available. In our experimentation, Fig. 6.45 shows that the EV is run using the same drive cycle and at almost the same speed along both the routes. The distance between A and B is approximately 600 meters and maintaining an average speed of 7km/hr, it takes 300 secs (5 mins) in both routes to reach the destination.

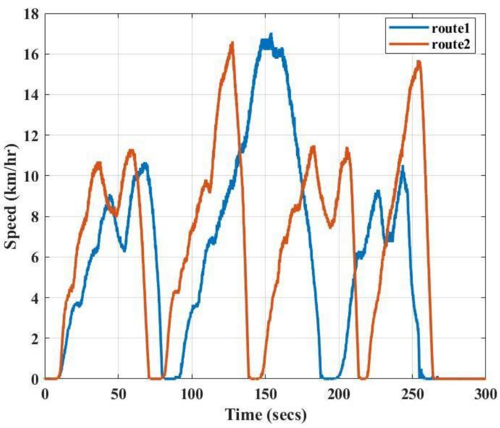

Fig.6.45 Driving cycle pattern of the test EV on both routes

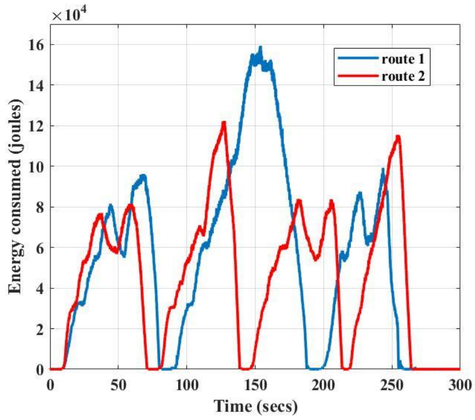

Fig.6.46 The energy consumption profile of the test EV along both routes

The energy consumption model is then used to calculate the total energy consumption during the trip and it can be well seen from Fig. 6.46 that despite being the same length route 1 consumes greater energy. The energy consumption in Route 1 is 45 KJ whereas that for route 2 is about 35 KJ. Route 1 consumes more energy as due to factors like different road conditions; the force on the wheels , the road grade and the average current consumption is more. Route 2 can thereby be called the more energy efficient and hence an eco-route.

ii. Case 2 :

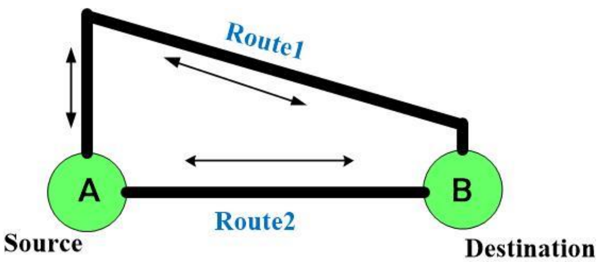

Fig.6.47 Illustration of two routes of different length from A to B

Case 2, as illustrated in Fig. 6.47, considers two routes from source A to destination B. Here, Route 1 is the longer route with less or almost no roadgrade whereas Route 2 is the shorter route with a higher percentage of roadgrade inclination present all along the route. Here also, the Delhi bus cycle has been used for experimentation purposes. The length of the shorter route is around 300 metres, which can be completed in 150 seconds considering an average speed of 7km/hr.The longer route is almost double the length, i.e., 600 metres, can be traversed in 300 if the road condition is same for both. For this experiment, using the equations (24) to (30), the total energy consumption of the test EV during both trips has been evaluated. Route 1 proves to be more energy efficient, although the distance of route 1 is longer than that of route 2. Route 1 can thereby be classified as an eco-route.

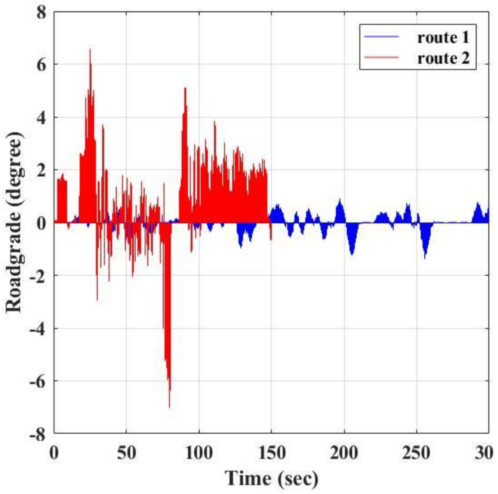

Fig.6.48 Comparison of the road grade profile of both the routes

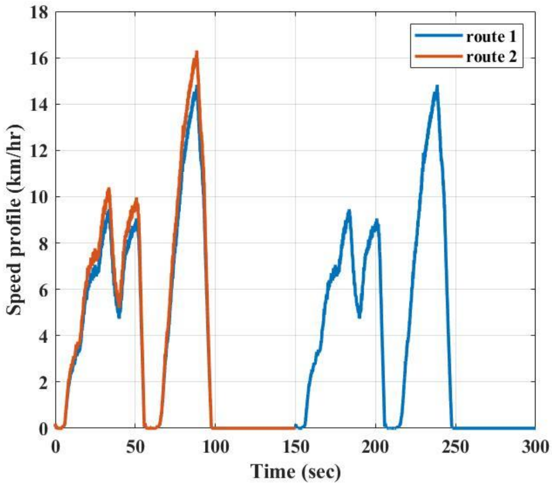

Fig.6.49 The speed profile followed in both routes during the trips

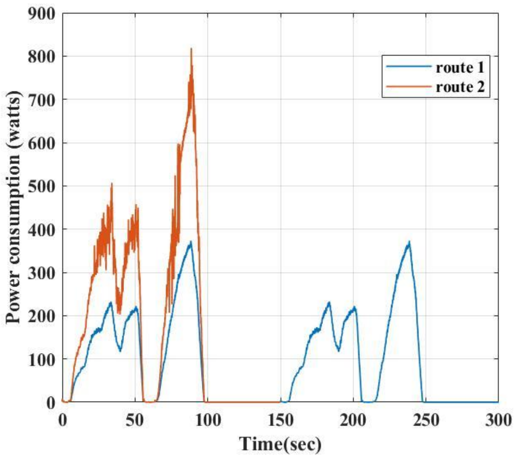

Fig.6.50 The power consumption profile of the test EV along both routes

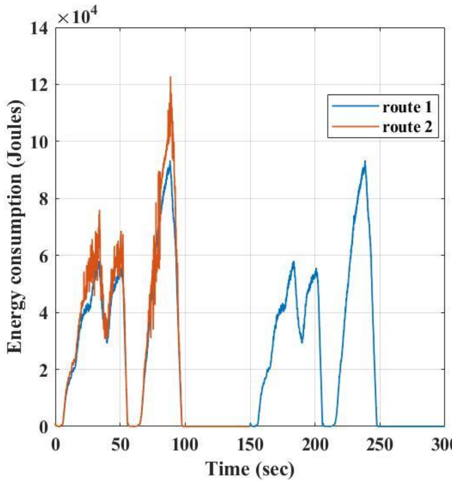

Fig.6.51 The energy consumption of the test EV on both routes

The road grade data has been collected using accelerometers connected to the test EV. The change in road grade is due to the fact that Route 2 consists of various crests and dips along the route due to the uneven road surface as well as the inclination present in the route. Fig. 6.48 shows the difference in road grade present on both routes. This experimentation was carried out to showcase the importance of road grade present in a route, which can be considered a crucial factor for eco-routing. The same driving cycle pattern has been used to drive the car along both routes, and it has also been assured that the average speed maintained during the trip is the same. The speed profile maintained while traversing both routes has been shown in Fig. 6.49. Theoritically, route 1 is longer, so it should take more time to reach B from A. Bus as far as energy efficiency is concerned, though Route 1 is longer, energy usage is lower than the shorter route. The calculation of power consumption highlights the contribution of road grade quite well, which has been plotted in Fig. 6.50. Due to higher grades and road unevenness, the force experienced at the wheels in route 2 is fairly higher than in route 1. This is because, due to the presence of road grade, more tractive effort is required, which in turn draws more energy from the battery source. The power consumption profiles of the routes show that the average power consumed in travelling the longer route is around 94 watts, whereas traversing the shorter route consumes an amount of 175 Watts.The energy consumption profile of the EV in both the routes have been illustrated in Fig.6.51. It can be clearly seen that the energy consumed in the longer route is averaged at around 23 KJ which is lesser than that of energy used in the shorter route, averaged to 27 kJ approximately. Since route 1 consumes less energy, it is considered the eco-route here.

This case can also be explained with an additional explanation which includes the Coulombic efficiency of the battery during maneuver. The shorter route mentioned here has roadgrade in it, which means that the EV travels uphill as well as downhill during its entire journey. Though short, when the EV treads uphill, the current consumption increases which leads to higher discharge of current from the battery. At higher dicharge rates however, the Coulombic efficiency of the battery decreases. Full battery capacity cannot be achieved at these rates. The decrease in the efficiency of the battery again adds to the increased energy consumption of the EV. The longer route however, achieves an average efficiency throughout leading to a lower energy usage even when the travel distance is high. It can therefore be termed as the eco-route. The mathematical expression for estimation of the total energy use has been described below:

$$Total\ energy = P * t * \eta_{reduced} \tag{48}$$

where power P is the product of the current consumed and the voltage, t is the time taken to travel that distance and $\eta_{redu\ ced}$ is the reduced coulombic efficiency of the battery.

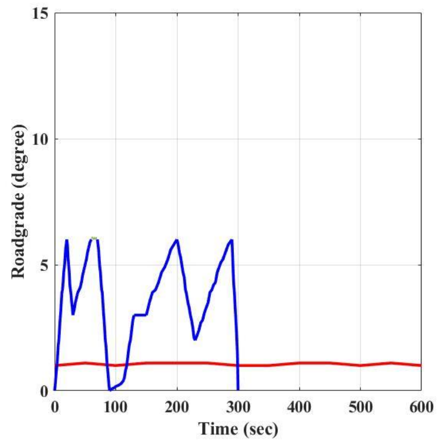

Fig.6.52 Portrayal of the two routes with and without roadgrade

Fig.6.52 illustrates the two routes wherein the long route is smooth and the shorter road is with crests and dips. The energy consumption of the long route is fairly simple where the EV is considered to be travelling at an average speed of 12km/hr. The current and the voltage data has been compiled to estimate that the energy consumed during the trip is around 3.5 kJ. For the shorter route it has been divided into segments of crests and dips. The energy of each segment was calculated individually and then summed to estimate the total rnergy consumption during the entire trip. The energy use is estimated to be around 4.2kJ.This proves that a shorter route may not always be energy-efficient. In this case the longer route conserves more energy and hence is the eco-route.

iii. Case 3:

Two routes of varying durations have been taken into consideration for this experimental study.It is postulated that both roadways possess smooth concrete surfaces, with the distinction being that the shorter road(Route 1) is dry while the longer road (Route 2) is dampened as a result of prevailing weather conditions. The propensity to choose the most efficient path to a desired location is inherent in human behaviour. The objective to establish in this context is that energy efficiency is vital in eco-routing navigation. The energy efficiency of a route may not always align with its shortest path. The power consumption profile of both route options throughout a journey has been elucidated using Figure 6.54. This analysis is based on rolling resistance experienced at the tyres while in motion. A road surface that is wet will necessitate a reduced amount of energy to counteract rolling resistance, resulting in a decrease in overall energy usage. Conversely, when going on a dry road, the rolling resistance coefficient of the tyres would elevate, leading to an augmented consumption of energy. The average power usage during traversal of the shorter route is recorded as around 133 Watts, however this value decreases to 70 Watts when the driver opts for the longer route. Integrating the power signal shows that the average energy consumption in the longer wet route is 17kJ. The mean consumption increases to around 20kJ if the EV traverses using the shorter route. This has been showcased in Fig.6.55. Hence, the lengthier route in this context functions as the route that is more energy efficient, or commonly referred to as the eco-route.

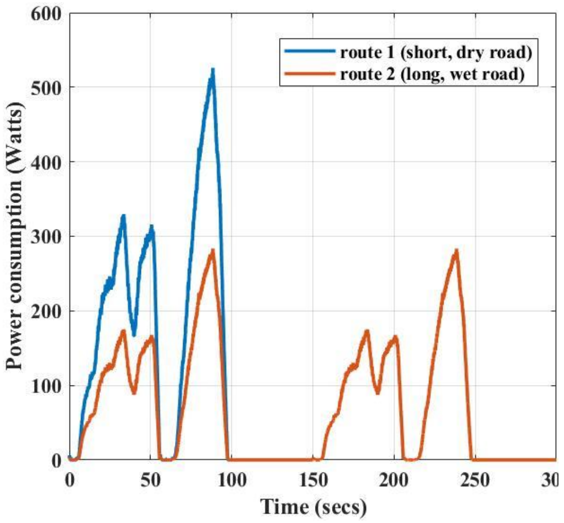

Fig.6.53 The power profile of the test EV along both routes

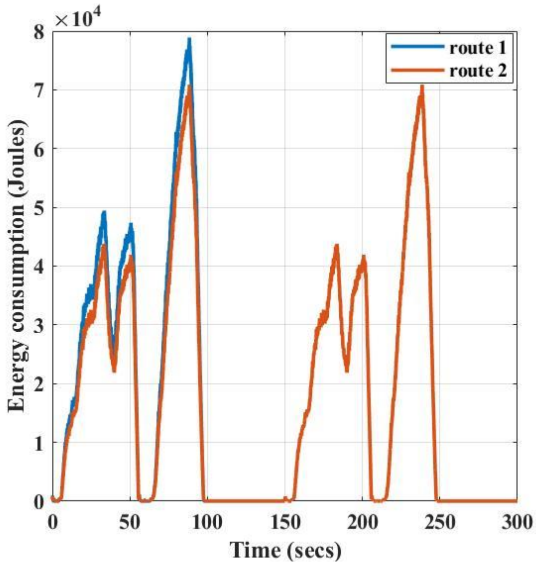

Fig.6.54 Energy consumption profile of both the route options available for the test EV

iv. Case 4:

The state of the traffic is one of many factors that affect how effective eco-routing navigation is in EVs. This scenario examines the impact of traffic on an environmentally friendly route. We investigate two distinct pathways of varying distances in order to arrive at a common endpoint. The shorter route frequently experiences greater traffic congestion in comparison to the longer route. In general, a navigation system often recommends that the driver select the route with the shortest distance. However, this approach differs when considering eco-routing. The longer route is seen as the eco-route because increased traffic on the shorter road necessitates that EVs remain on the road for a longer duration, leading to greater battery depletion and consequently higher energy utilisation. A road characterised by lower traffic volume will not only require less time for travel but also result in reduced energy consumption, thereby leading to an extended range for electric vehicles.

v. Case 5:

This study examines the impact of crosswinds while determining an energy-efficient route. In this assessment, two routes of equal length have been taken into account. Both routes require approximately 5 minutes reaching the destination. Route 1 is characterised by a prevailing crosswind with an approximate velocity of 5km/hr, while Route 2 is devoid of any. The power consumption on both routes exhibits a notable difference, as depicted in Figure 6.55, despite their equal length. The underlying rationale for this phenomenon is that the existence of crosswinds along the trajectory amplifies the aerodynamic resistance of the EV, thus augmenting its energy consumption. The average power consumption in Route 1 is approximately 121 watts, which reduces to 87 watts if Route 2 is chosen for the maneuver. Based on the given scenario, it can be inferred that selecting the path with lower wind resistance will result in greater energy efficiency, therefore qualifying it as the environmentally conscious or eco-route.

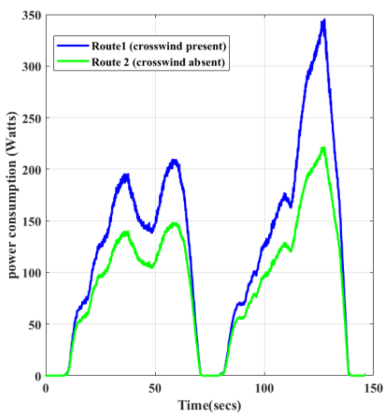

Fig.6.55 Power consumption in presence and in absence of crosswinds

Eco-routing is mainly conceptualised on the basis that longer travel times can be traded for lower energy. In the above cases, only factor has been highlighted in each case, while the rest are considered to be exactly the same on both routes. Energy minimization is vital in the case of EVs, and therefore, taking the route which consumes less energy will prove beneficial in extending the range of the vehicle. For ease of demonstration, the path of the road considered is very small, and so the energy difference is also small. But in practical cases, when an EV has to cover a long distance, the energy consumption difference will be quite considerable, and chooding an eco-route will prove advantageous for the EV and the environment at large.

6.9.4. Prediction of energy consumption using neural networking

The energy consumption prediction in EVs is a nonlinear control problem which in general requires application of various computational or approximative procedures for establishing a solution [38].It has already been mentioned that the model has been created using nntool in MATLAB Simulink environment. The training procedure employs the Levenberg-Marquardt optimisation algorithm to iteratively adjust the weight and bias parameters. The selection of this particular function is based on its frequent utilisation as the most efficient approach for back propagation in supervised learning. The model underwent training and subsequent testing to forecast the energy consumption of an EV. The performance of the network has been measured according to the mean of squared errors. It takes a neural network, a matrix or cell array of targets, a matrix or cell array of outputs and error weights to calculate the mean squared error.The performance of the model has been illustrated in Fig. 6.56. The regression and the training state of the network have been depicted in Fig. 6.57and Fig. 6.58 respectively. It can be observed from Fig. 6.59 that the network has been trained quite well and it appropriately predicts values. The curve shows a comparison of the trained network outputs and actual output data. Since the model is able to predict the values for energy usage, this model can be used for the prediction of consumed energy during a trip alongwith the estimation of the range of the EV.

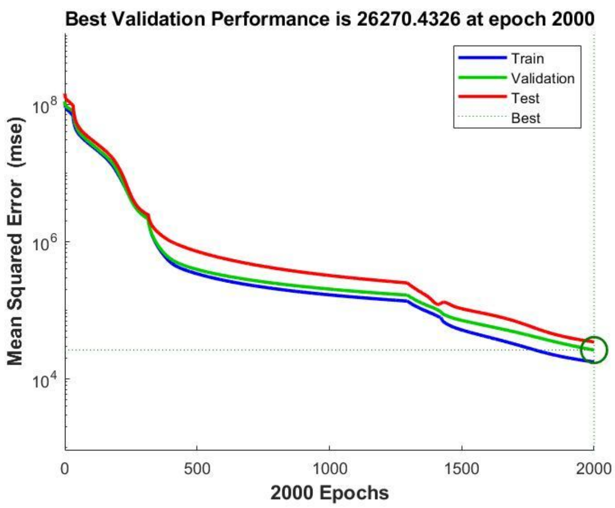

Fig.6.56 Performance curve of the NN model

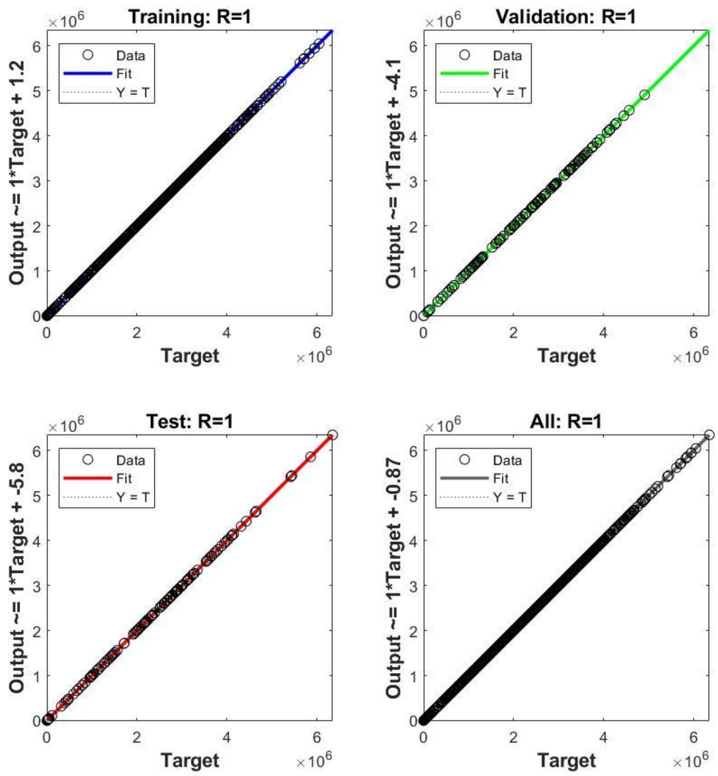

Fig.6.57 Regression curve of the NN model

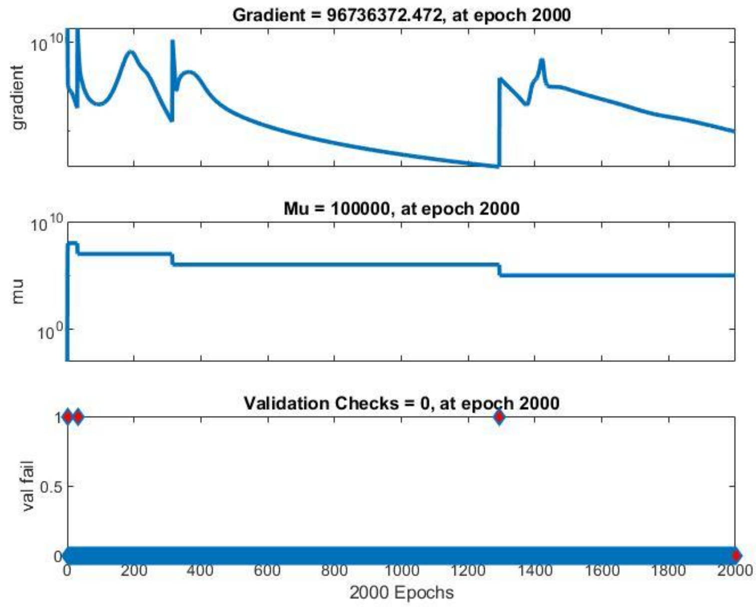

Fig.6.58 Training state of the NN model

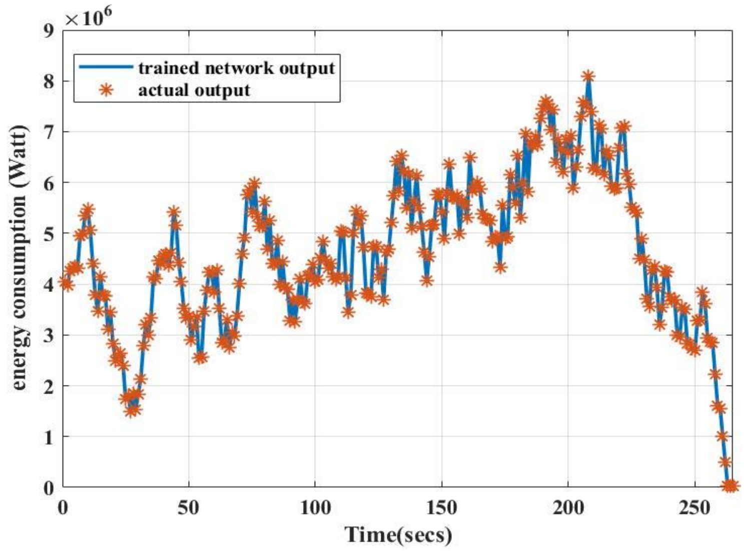

Fig.6.59 Comparison of trained data and road-test data using the NN model

6.10. Conclusion

This chapter summarises the importance of energy consumption estimation in eco-routing navigation systems for electric vehicles. An energy consumption model based on road load and vehicle dynamics has been developed and used for measuring the energy consumed during a trip. The energy obtained is then used for the determination of eco-routes in cases where there is more than one route available to reach the destination. Evaluation of the model has been performed using real-time data obtained from on-road tests of a test vehicle prototype that has been designed and built as a part of this research work. The prototype is a dynamic test bed, which is a lightweight EV powered by a lithium ion battery source. It is independent rear wheel driven and uses PMDC motors for its operation. To attain the main aim of calculating the energy consumption of an EV, different sensors were installed in the test vehicle, from which data on various parameters was obtained.The different parameters are voltage across motors, the amount of current consumed, load on each of the wheels of the vehicle, tilt or pitch of the EV, speed, and acceleration of the EV. The data was then processed using a MATLAB environment, and using the road load model that was earlier developed, the power consumption at every instant of the trip was obtained. The energy consumption of the vehicle has also been derived. The range of the EV was estimated, which is almost a pre-requisite in the determination of an eco-route.It was observed that using the Delhi bus cycle, an average of 7 km/hr is achieved, which gives a range of around 18 km when a 40 Ah lithium ion battery is used. A demonstration of an eco-route has also been performed by showcasing two cases. Case 1 had two routes of the same length, which showed that the presence of different road conditions or grades would result in different energy consumption even though all other factors were assumed to be the same. Case 2 illustrated an eco-route that traded travel time for lower energy consumption. The energy consumption of the test EV was calculated using the road load model, which was earlier developed. The parameters needed for the estimation were obtained through different sensors installed in the test vehicle. The data was then processed using a MATLAB environment. The significance of using different driving cycles and paths with different road grades was also analysed. It was found that using a different driving cycle resulted in a different speed profile to reach the same destination. This feature affects the remaining range of the vehicle while taking a trip. It has also been observed that the inclusion of road grade while estimating energy use increases energy consumption, thereby drawing the conclusion that flatter and smoother roads will lead to lower energy consumption for the EV. The proposed technique is simple, cost-friendly and since minimal circuitry is involved, it is quite user friendly too. Energy efficiency is a dynamic problem as it depends on various factors that have been discussed. Its precise prediction is, therefore, difficult. A neural network model has thereby been included, which can be used for prediction of the energy consumption of the EV on unknown routes during a manoeuvre. Results obtained from the model clearly show that the neural network can correctly predict the energy consumption of an electric vehicle. Future works will include the use of dynamic non-linear factors affecting energy usage in the neural network model for the prediction of energy consumption during a manoeuvre. The prediction values can then be effectively incorporated with the energy consumption model and GPS techniques to develop a smart eco-routing system that can be universally used onboard electric vehicles.

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