Intelligent driving range predictor for green transport

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Abstract. Deployment of large number of electric vehicles has been planned in the coming years for improving fuel economy and to meet emission standards. Government of India plans to introduce subsidy/tax rebate/incentive for EV users who utilizes electrical energy in an optimal manner. The major anxiety of people opting for EV is low driving range and the accessibility of connection to the utility grid. If a facility is available to monitor battery parameters to compute power requirements and to list out nearest charging stations, it will help EV users a lot. This paper proposes an intelligent monitoring and predicting scheme for battery state of charge, driving range and other useful information. The scheme is validated with MATLAB/Simulink simulation results.

1. Introduction

United Nation’s Intergovernmental panel on climate change (IPCC) report in October 2018 describes measures to avoid the consequences of climate change. It claimed that sea level rise, food shortages and widespread drought can be avoided if the emissions are reduced by 45% from 2010 and 100% by 2050. 25% of total energy consumption is constituted by the transportation sector. Hence transportation electrification can contribute to large amounts of GHG reduction. Major limitations of electric vehicles are anxiety regarding driving range and accessibility to the charging infrastructure. Recently Nissan Leaf, Chevrolet Bolt and Tesla launched their vehicles with a driving range of 150 miles, 238 miles and 300 miles on a single charge. But to ensure economy, an intelligent energy management system which is capable of predicting power requirements or SoC of the battery, and options for selecting nearest battery EV charging station for the selected trip is highly advantageous. Indian government is planning to shift to electric vehicles by 2030, so that the dependence on oil and environmental pollution will get reduced to a large extent. Government plans to support establishment of EV charging stations, to give subsidies for purchasing EVs and to reduce road tax. With integration of large number of renewable energy plants and modern power electronic equipment, electric vehicles will be cheaper and the operating cost also will be highly reduced.

As per National Electric Mobility Mission Plan (NEMMP) 2020, Indian government targets to deploy 5-7 million electric vehicles and to decline vehicular emission by 1.3% in the country by 2020. The Government of India has announced the Deen-Dayal scheme in June 2014 for financing and procurement of battery rickshaws. Motor Vehicles Bill (March 2015) established these vehicles as a valid commercial transport. It is also envisaged that EV penetration will help to reduce 50% of carbon emission by 2030. However intelligent planning, proper maintaining and control of charging infrastructure is necessary for successful deployment of large number of electric vehicles.

Electric vehicles are of different types such as two wheelers, three wheelers, cars and buses. It can be pure electric vehicle (Battery EV) or plug-in hybrid vehicle (combination of EV and ICE). Battery is the
major component of electric vehicle which varies in their characteristics, energy density, weight and cost. Batteries commonly used in EVs are Lead Acid, Nickel-Cadmium, Nickel Metal Hydride and Lithium-ion. A dedicated battery management system is to be associated with the battery to instantaneously measure and indicate its key parameters such as voltage, current, temperature and SoC so that the EV owner can make a decision on route for travel and opt for charging stations [1].

This paper presents an intelligent planning scheme for the routing of electric vehicles in an optimal and economical way. Here the user gets to select a route by specifying the source and destination locations in the user interface [2]. The drive cycle which the EV will have to follow at that time through that road is obtained from the model and the power requirement calculations are made. Power flow diagram in electric vehicles, computation of power requirement in each driving trip, SoC requirements etc. are described in the succeeding sections. Figure 1 displays the overall block diagram of the driving range estimator model.

2. Drive cycle
The power consumed by an EV is largely decided by the velocity with which it travels. The drive cycle which the EV will follow at any time through any user defined road can be predicted using a neural network or any data driven model [3,4]. In this paper the predicted drive cycle is obtained from the model. In the next section the total power requirements in an electric vehicle is computed.

3. Power consumption on a given route
The power consumed by an electric vehicle depends on environmental conditions of the route, traffic existing in the route, power used by auxiliary load etc. Figure 2 shows the power flow diagram in an EV.

Figure 1. Block diagram of range estimation block.

Figure 2. Power flow diagram in an EV.
3.1. Tractive power ($P_{\text{tractive}}$)

The tractive power consists of work done against rolling resistance, aerodynamic work, change in kinetic energy and change in potential energy along the route of travel [5]. These terms can be calculated as given in the table 1. The variables $m$ and $V$ are the total mass of the EV and velocity at any time $t$ obtained from drive cycle respectively. The route connecting source and destination was split into a definite number of equidistant segments and the below calculations were made.

| Power component                                | Equation                                      | Variables                      |
|-----------------------------------------------|-----------------------------------------------|--------------------------------|
| Power to overcome rolling resistance ($P_{\text{roll}}$) | $P_{\text{roll}} = mgC_{r,\text{eff}} V$ | $C_{r,\text{eff}}$ – coefficient of rolling resistance, $g$ – acceleration due to gravity. |
| Power to overcome aerodynamic drag ($P_{\text{aero}}$) | $P_{\text{aero}} = 0.5 \rho_{\text{air}} C_d A_f (V+V_{\text{wind}})^2 V$ | $\rho_{\text{air}}$ – density of air, $C_d$ – drag coefficient, $A_f$ – frontal area, $V_{\text{wind}}$ – wind velocity. |
| Power associated with change in potential energy ($P_{\text{PE}}$) | $P_{\text{PE}} = \frac{1}{t_{\text{seg}}} mg(h_k-h_{k-1})$ | $h_k$ is the elevation at the starting of segment $k$, $t_{\text{seg}}$ is the time taken for travelling between adjacent segments. |
| Power associated with change in kinetic energy ($P_{\text{KE}}$) | $P_{\text{KE}} = \frac{1}{2t_{\text{seg}}} m(v_k^2-v_{k-1}^2)$ | $v_k$ is the velocity of EV at the starting point of $k^{th}$ segment. |

$P_{\text{tractive}}$ can then be expressed as:

$$P_{\text{tractive}} = (P_{\text{roll}} + P_{\text{aero}} + P_{\text{PE}} + P_{\text{KE}}) \frac{1}{\eta_{\text{trans}}}$$

considering a transmission efficiency of $\eta_{\text{trans}}$.

For calculating the power associated with change in potential energy, the route is split into a number of road segments and the elevation at each road segment is obtained from Google Elevation Service API by passing the latitude and longitude details of the specific location.

3.2. Inverter & Induction motor losses ($P_{\text{inv}}$ & $P_{\text{ind}}$)

When a switch in the inverter leg is turned ON and OFF repeatedly and continuously switching and conduction losses occur in them. The losses that occur in inverter and induction motor for different speed ranges are given in the table 2.
Table 2. Losses.

| Loss component                  | Equation                                                                 | Variables                                                                 |
|---------------------------------|--------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Inverter losses (P_{inv})       | \( P_{\text{inverter}} = P_{\text{conduction}} + P_{\text{switching}} \) | \( I_Q \) is the switch current, \( R_{CE,\text{on}} \) is the on state resistance of the switch and \( V_{CE} \) is the voltage drop across the switch, \( f_{\text{swi}} \) is the switching frequency, \( t_{\text{on,sw}} \) is the turn on rise time, \( t_{\text{off,sw}} \) is the turn off fall time. |
|                                 | \( P_{\text{conduction}} = V_{CE} I_{Q,\text{avg}} + R_{CE,\text{on}} I_{Q,\text{rms}}^2 \) | \( P_{\text{switching}} = \frac{1}{2} V_{Q} I_{Q} f_{\text{swi}} (t_{\text{on,sw}} + t_{\text{off,sw}}) \) |
| Induction motor losses (P_{ind}) | \( P_{\text{ind}} = k_1 T^2 + k_2 \omega + k_3 \omega^3 + C \) | \( k_1, k_2, k_3 \) and \( C \) are coefficient of proportional relation between torque and current, added coefficient of friction and iron losses, windage coefficient and constant loss value [6]. |

3.3. Power consumed by auxiliary loads (P_{aux})

The power required for auxiliary loads is also taken from the battery of EV. Some of the auxiliary power requirements in an EV are given in the table 3.

Table 3. Power consumed by auxiliary loads.

| Power component                | Equation                                                                 | Comments                                                                 |
|--------------------------------|--------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Lighting (P_{lighting})        | \( P_{\text{lighting}} = \begin{cases} \bar{P}_t, \text{night time travel} \\ 0, \text{day time travel} \end{cases} \) | Lighting is required during night time journey and the power for this is consumed from EV battery. |
| Air-conditioner A/C (P_{AC})   | \( P_{\text{AC}} = P_{\text{cooling}}(T_{\text{cabin}} - T_{\text{req}}), \text{cooling} \) \( P_{\text{heating}}(T_{\text{req}} - T_{\text{cabin}}), \text{heating} \) | Air conditioners are used to maintain required temperature inside the cabin of EV. \( P_{\text{heating}} \), \( P_{\text{cooling}} \) are the power required for heating, cooling (per degree) and \( T_{\text{cabin}}, T_{\text{req}} \) are the actual cabin temperature and required cabin temperature. |
| Wipers (P_{wip})               | \( P_{\text{wip}} = P(X=\text{rain}) P_{\text{wipers}} \) | The probability that it will rain in a particular region and the strength of rainfall has a great influence on the time span of working of wipers. \( P(X=\text{rain}) \) is the probability that it will rain and \( P_{\text{wipers}} \) is the power consumed by wipers for working continuously. |
| Indicator (P_{indicator})      | \( P_{\text{indicator}} = n P_{\text{turn}} \) | When an EV takes a left or right turn and the indicators are turned ON, power is taken from the battery. \( n \) is the number of turns per road segment obtained from Google Maps. |
The total power consumed by auxiliary loads can then be calculated as:

\[ P_{\text{aux}} = P_{\text{lighting}} + P_{\text{AC}} + P_{\text{wipers}} + P_{\text{indicator}} \]

4. Battery model

Generally lithium ion batteries are used in electric vehicles due to high energy density and less self-discharge rates. With the help of a first order thevenin battery model the state and measurement equations were derived and the EKF algorithm was applied for SoC estimation. Since the dynamic characteristics can be simulated accurately thevenin battery model was taken for analysis [7]. Figure 3 shows the thevenin battery model of lithium ion battery pack.

![Thevenin battery model](image)

The parameters \( I, V_o, V_{oc}, R_i, R_d, C_b, C_d \) are charging/discharging current, output voltage, open circuit voltage, internal resistance, polarization resistance, bulk capacitance and surface capacitance of the battery model respectively. From the battery model following equations are obtained [8].

\[ V_{oc} = \frac{1}{C_b} \]  
\[ V_d = \frac{1}{C_d} - \frac{V_d}{R_d C_d} \]  
\[ V_o = V_{oc} + V_d + IR_i \]

Open circuit voltage can be expressed as a non-linear function of battery state of charge. Hence the equation \( V_{oc} = a \text{SoC} + b \) can be written, where \( a \) and \( b \) vary with state of charge and ambient temperature and hence are not constants. Finally in matrix form the state and measurement equations of the thevenin battery model can then be expressed as

\[
\begin{bmatrix}
\text{SoC} \\
V_d
\end{bmatrix} = \begin{bmatrix}
\frac{1}{C_b} \\
\frac{1}{C_d} - \frac{V_d}{R_d C_d}
\end{bmatrix} \begin{bmatrix}
\text{SoC} + b + V_d + IR_i
\end{bmatrix}
\]

5. Extended Kalman Filter algorithm

Kalman filter is a linear state estimator. Since the battery model is non-linear, Kalman filter cannot be used directly. Hence Taylor series approximation of the battery model at its operating points is taken to convert it into linear and then Kalman filter algorithm is applied. Hence the name Extended Kalman Filter was given as it as an extension of Kalman filter. The thevenin battery model can be represented as:

\[ \dot{x} = s(x,u) + q \text{ and } y = m(x,u) + r \]

where \( x \) is the state matrix, \( y \) is the output matrix, \( q \) is the process noise, \( r \) is the measurement noise, \( s(x,u) \) and \( m(x,u) \) are the state and measurement equations respectively. Then it can be deduced that:

\[ s(x,u) = \begin{bmatrix}
s_1 \\
s_2
\end{bmatrix} = \begin{bmatrix}
\frac{1}{C_b} \\
\frac{1}{C_d} - \frac{V_d}{R_d C_d}
\end{bmatrix} \text{ and } m(x,u) = a \text{SoC} + b + V_d + IR_i \]

The Kalman filter algorithm consists of two steps namely prediction step and update step. In prediction step the initial state, error covariance, process noise and measurement noise are predicted. Later in the
update step Kalman gain is found and states of the system and error covariance are updated. Once after taking Taylor series approximation and linearization, the battery model can be represented as [9]:

\[
\dot{x} = A_m x + B_m u \quad \text{and} \quad y = C_m x + D_m u, \quad \text{where}
\]

\[
A_m = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{R_c C_d} \end{bmatrix}, \quad B_m = \begin{bmatrix} \frac{1}{R_c} \\ 1 \end{bmatrix}, \quad C_m = \begin{bmatrix} a & 1 \end{bmatrix}, \quad D_m = R_i
\]

A battery pack in an EV consists of cells connected in series as well as in parallel fashion to obtain the required voltage and capacity rating of the battery pack. A battery management system will be monitoring each cell in the battery pack by collecting current and voltage data and thereby ensuring cell balancing. In this paper a single Lithium-ion 1RC cell is taken and discharged using a current pulse. Then the SoC of the cell was estimated using Extended Kalman Filter in MATLAB/Simulink. In real time SoC of each cell can be estimated using EKF and the battery pack SoC can be found out. Figure 4 shows the simulink model for SoC estimation.

![Simulink model for SoC estimation](image)

Figure 4. SoC estimation using Extended Kalman Filter.

The next section explains how to find out the final SoC after the trip considering all the power requirements in the EV.

6. SoC determination of battery

The total power consumed from the EV battery can be obtained as:

\[
P_{\text{battery}} = P_{\text{tractive}} + P_{\text{inverter}} + P_{\text{end}} + P_{\text{aux}}
\]

and the current drawn from the battery is given by

\[
I_{\text{battery}} = \frac{P_{\text{battery}}}{V_{\text{battery}}}
\]

where \(V_{\text{battery}}\) is the voltage of battery pack. The final SoC at the end of the trip is obtained as

\[
\text{SoC}_{\text{final}} = \text{SoC}_{\text{initial}} - \frac{1}{\text{battery capacity}} \sum_{k=0}^{n} I_{\text{battery}, k} I_k
\]
where \( \text{SoC}_{\text{initial}} \) is the initial value of SoC obtained from Kalman filter block, \( I_{\text{battery, } k} \) and \( t_k \) are the current consumed (A) and time spent (hours) in between \( k \) and \( k-1 \) segments.

7. Remaining range estimation
There exists three scenarios depending on the selection of destination location. Those scenarios are given in the table 4.

| Scenario                                                                 | Drivable trip distance                                    | Remaining range after trip |
|-------------------------------------------------------------------------|------------------------------------------------------------|----------------------------|
| SoC becomes minimum allowed value exactly at destination.               | Distance between source and destination.                   | 0 kms                      |
| SoC becomes the minimum allowed value at a location A between source and| Distance between source and the location A.                | 0 kms                      |
| destination.                                                            |                                                            |                            |
| SoC is more than the minimum allowed value, at destination.            | Distance between source and destination.                   | History based range estimation |

In the third scenario battery SoC is available even after the trip selected by the user is over. The range of the EV in this case depends upon the next route user is selecting. In case user is not selecting any routes, the knowledge about next source and destination is not known to the system. Hence a history based range estimation is employed here. An average energy consumption (AEC) is found out and the remaining range is predicted in this scenario. The remaining range can then be expressed as [10]

\[
\text{Remaining range} = 100 \text{ km} \frac{E - \Delta E}{\text{AEC}}
\]

where \( E \) is energy available in battery and \( \Delta E \) is the energy consumed between destination and current location.

8. Simulation results
The SoC of a single Lithium-ion 1RC cell was estimated using EKF. The estimated value was found to be following the actual value with an error of 0.01. Actual value vs estimated value, the error in estimation etc. are displayed in figures 5 and 6 respectively.
A simulink model was created to find out the remaining range and final SoC of the EV after the trip using the parameters shown in the table 5. The model is simulated from a location A to B, considering the elevation details of the route and assuming that the EV drive cycle is obtained from the drive cycle generator model with values of initial soc and max allowed soc lower limit as 0.75 and 0.2 respectively. The distance between A and B was 114.33 kms. A real time dataset was taken [11] to compare the real energy consumption and simulated energy consumption and it was found that the real value is 19.28KWh and simulated value is 19.36 KWh. The simulink model predicted the remaining range after the trip as 0 kms and the distance EV could travel (with an initial soc of 0.75) as 82.05 kms, which is in accordance with the second driving scenario.

The power consumption model of EV, comparison of real time power & simulated power, variation of SoC with time and drive cycle are displayed in figures 7, 8, 9 and 10.

Table 5. EV parameters.

| Parameter               | Symbol | Value       |
|-------------------------|--------|-------------|
| Total mass of the EV    | m      | 1558 kg     |
| Acceleration due to gravity | g    | 9.8 m/sec²  |
| Density of air          | ρ_air  | 1.225 kg/m³ |
| Frontal area            | A_f    | 2.5 m²      |
| Drag coefficient        | C_d    | 0.3         |
Figure 7. Power consumption model.

Figure 8. Power consumption: Real time vs Simulation.

Figure 9. State of charge vs Time.
9. Conclusion

In this study two simulink models were built to estimate the SoC of Lithium-ion cell and to predict the remaining range of the EV at any time. The simulation results obtained were found to be matching with the real time driving results. The model was able to predict SoC with an error of 0.01. The range predictor model considered all power requirements in the EV and was able to predict the final SoC after the trip as well as the remaining range after the trip. Using EV’s current GPS location nearby charging stations can be found out and displayed in the user interface. If the model gets an idea about the power rating of charger in these EV stations, the time required for charging to a specific SoC limit can also be found out.

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