Assessment of an Electric Vehicle Powertrain Model Based on Real-World Driving and Charging Cycles

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Abstract—An analytical model for an electric vehicle (EV) powertrain has been developed in this paper to study the vehicular dynamics, based on a Nissan Leaf EV. The electrical components of the powertrain include a battery pack, a battery management system (BMS), a DC/DC converter, a DC/AC inverter, a permanent magnet synchronous motor (PMSM), and a control system while the mechanical system consists of power transmissions, axial shaft and vehicle wheels. The driving performance of the EV is studied through the real-world driving tests and simulation tests in Matlab/Simulink. In the analytical model, the vehicular dynamics is evaluated against changes in the vehicle velocity and acceleration, state of charge (SOC) of the battery, and the motor output power. Finally, a number of EVs are introduced in the system to optimize the power dispatch. The greenhouse gas emissions of EVs are analyzed under various driving and charging conditions, and compared with conventional internal combustion engine (ICE) vehicles. For a given driving cycle, Nissan Leaf can reduce CO₂ emissions by 70%, depending on its duty cycle and the way electricity is supplied.

Index Terms- Analytical model, electric vehicles, greenhouse gas emissions, powertrain, Nissan Leaf, V2G.

I. INTRODUCTION

Concerns over global warming and depleting fossil fuels have led to the rapid development of electric vehicles (EVs) to replace internal combustion engine (ICE) vehicles. Presently, major industrial countries have published their energy policies and developed economic incentives to encourage the uptake of EVs [1]-[3]. The electrical components of the EV powertrain include a battery pack, a DC/DC converter, a DC/AC converter, an electrical machine and a control system [4][5]. The pure battery EVs utilise batteries as the power source to drive the vehicle [6]. They have zero atmospheric emissions and represent a means of eco-friendly personal transportation. On the contrary, ICE vehicles and hybrid EVs employ ICE engines as the whole or part of their power source, and thus generate CO₂ emissions to some extent. The use of energy storage components can ensure a stable power supply and a quick response to the demand [7]-[9]. For example, fuel cell hybrid electric vehicles (FCHEVs) have a controllable input power from fuel cells and a supercapacitor to respond to the demand. But they are complex in control and costly in the marketplace. For instance, only 200 units of Toyota Mirai (FCHEV) are sold in Europe [10]. In the UK, there are 6008 charging stations for PEVs while there are only 11 hydrogen stations for FCEVs. In terms of EV motor system, four types of electrical machines are commonly used in EVs. Compared with brushed DC motors, induction motors (IMs) and switched reluctance motors (SRMs), permanent magnet synchronous motors (PMSMs) have their advantages, such as better controllability, lighter weight, higher power density and efficiency. In this work, the EV is Nissan Leaf which utilizes a PMSM [11]-[13]. It is a pure EV and is one of the best-sellers in Europe. More than 300,000 cars are sold since its introduction in 2010, including 68,000 in the European market [14]. The Nissan Leaf powertrain includes electrical and mechanical systems. In the literature, EV powertrains are generally modeled by mechanical systems while electrical systems are overlooked [15]-[18]. In this paper, an extensive powertrain model has been built by analytical methods and Matlab/Simulink to include electrical systems.

II. SIMULATION OF EV POWERTRAIN DYNAMIC SYSTEM

A conventional EV powertrain is shown in Fig. 1. The electrical system consists of a PMSM, a battery management unit (BMU), one battery pack, a DC-DC converter and a DC-AC inverter, and an electronic controller module. The mechanical system includes a transmission system, an axle shaft and wheels train system. The vehicle speed, motor torque and speed, and battery state of charge SOC are monitored in real time. The online route and vehicle dashboard are presented in Fig. 2.
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acquire the minimum mean squared error estimation [19][20]. The Kalman filter (KF) is used to estimate the SOC of the battery as it indicates the health status. The BMS, it is convenient to update the parameters in real time. Assuming that $z_j = S_j$ and considering the equivalent coulombic efficiency, the state function can be derived by,

$$
\hat{z}_{k+1} = \begin{cases} 
\hat{z}_k - Kq_s \frac{I_k \Delta t}{C} + w_k, & I_k < 0 \\
\hat{z}_k - Kq_s \frac{I_k \Delta t}{C} + w_k, & I_k > 0 
\end{cases}
$$

where $q_s$ is the equivalent charge for discharging and $q_d$ is the equivalent discharge efficiency. The base coulombic efficiency in Eq. 4 is $\gamma_c/3$.

The combined function based on measurements is

$$
y_k = g(\hat{z}_k, z_k) + v_k
$$

where $K_0, K_1, K_2, K_3$ and $K_4$ are the fitting coefficients, $R$ is the internal resistance and $\gamma_v$ is the measurement noise. According to Eqs. 4 and 5, a nonlinear discrete-time state space battery model is established. Therefore, the AEKF method would be adopted for estimating the SOC.

The SOC state is estimated by:

$$
\hat{z}_{k/\hat{k}-1} = \begin{cases} 
\frac{\hat{z}_{k-1/\hat{k}-1} - \frac{I_k \Delta t}{C} + q_k}{1 - \hat{z}_{k/\hat{k}-1}} & I_k < 0 \\
\frac{\hat{z}_{k-1/\hat{k}-1} - \frac{I_k \Delta t}{C} + q_k}{1 - \hat{z}_{k/\hat{k}-1}} & I_k > 0 
\end{cases}
$$

The error covariance is:

$$
P_{k/\hat{k}-1} = P_{k-1/\hat{k}-1} + Q_k
$$

The Kalman gain capacitor and coefficient are:

$$
K_k = P_{k/\hat{k}-1} C_k^{-1} \left[ C_k P_{k/\hat{k}-1} C_k^{-1} + R_k \right]^{-1}
$$

The measured SOC state is given by:

$$
\hat{z}_k = \hat{z}_{k/\hat{k}-1} - K_k (I - K_k C_k) P_{k/\hat{k}-1}
$$

The error covariance measurement is:

$$
P_{k/\hat{k}} = (I - K_k C_k) P_{k/\hat{k}-1}
$$

respectively. $f(z_j, U_j)$ is a nonlinear state transition function. $y_j$ is the measurable output and $g(z_j, U_j)$ is the nonlinear state transition function. $v_j$ is an independent Gaussian noise process with the statistical properties in the function. By using an AEKF method for the BMS, the discrete function of SOC can be transferred.

$$
S_{j+1} = S_j - \frac{v_j \Delta t}{C_n} 
$$

where $S_j$ and $S_{j+1}$ are the SOC at time $j$. $C_n$ is the nominal capacity, and $I_k$ is the current at time $j$. The current would be positive while discharging and negative while charging. $\gamma$ is the coulombic efficiency. Normally, $\gamma = 1$ for discharging and $\gamma < 1$ for charging in standard conditions.
modules are connected in series to form a battery pack. The electrical characteristics of battery cells are given in Table I. The cell voltage is rated at 3.75 V but can reach 4.2 V. The battery pack is arranged into 3 sections. One section contains 24 modules in the center of the pack. Two other sections of 12 modules each are connected in series with the central section on the two sides. The battery pack voltage is rated at 360V and its capacity is 24 kWh.

C. PMSM Model Development

In the EV powertrain, a high-efficiency PMSM is used and is powered by the battery pack through a three-phase DC-AC inverter [21]. The state space equations of a PMSM in the synchronous d-q reference frame are presented by

\[
\begin{align*}
\frac{di_d}{dt} &= \frac{1}{L_s} [U_d - R_s i_d - \omega_r L_q i_q] \\
\frac{di_q}{dt} &= \frac{1}{L_s} [U_q - R_s i_q - \omega_r L_d i_d - \omega_r \varphi_f]
\end{align*}
\]

where \(R_s\) and \(L_s\) are the stator-phase resistance and inductance, respectively. \(i_d\) and \(i_q\) are the \(d\)- and \(q\)-axis stator currents, and \(\omega_r\) is the rotor electrical speed, respectively. \(U_d\) and \(U_q\) are the stator voltages in the \(d\)-\(q\) reference frame, and \(\varphi_f\) is the rotor flux generated by the permanent magnets, respectively. A discrete-time model is applied for calculating the \(d\)-\(q\) reference currents in a sampling period in the vector control. By utilising a small sampling interval, the PMSM can be modeled in a discrete time, which is called Forward Euler discretization. The expression of the discrete-time equivalent equation is given by:

\[
\begin{align*}
i_d(j+1) &= i_d(j) + \frac{T_s}{L_s} [U_d(j) - R_s i_d(j) + E_d(j)] \\
i_q(j+1) &= i_q(j) + \frac{T_s}{L_s} [U_q(j) - R_s i_q(j) + E_q(j)] \\
E_d(j) &= \omega_r(j) L_q i_q(j) \\
E_q(j) &= \omega_r(j) L_d i_d(j) - \omega_r(j) \varphi_f
\end{align*}
\]

where \(E_d(j)\) and \(E_q(j)\) are the \(d\)- and \(q\)-axis back electromotive force (EMF) at the \(j\)th sampling instant; \(i_d(j)\) and \(i_q(j)\) are the \(d\)- and \(q\)-axis state currents at the \(j\)th sampling instant; \(U_d(j)\) and \(U_q(j)\) are the \(d\)- and \(q\)-axis state voltages at the \(j\)th sampling instant; \(i_d(j+1)\) and \(i_q(j+1)\) are the \(d\)- and \(q\)-axis state currents at the \((j+1)\)th sampling instant; \(U_d(j)\) and \(U_q(j)\) are the \(d\)- and \(q\)-axis state voltages at the \(j\)th sampling instant, \(T_s\) is the sampling period in the discrete-time model, respectively. The specifications of the PMSM are presented in Table II.

TABLE II CHARACTERISTICS OF NISSAN LEAF ELECTRICAL MOTOR

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated power</td>
<td>80 kW</td>
</tr>
<tr>
<td>Peak torque</td>
<td>280 Nm</td>
</tr>
<tr>
<td>Peak speed</td>
<td>10,390 rpm</td>
</tr>
<tr>
<td>Mass</td>
<td>56 kg</td>
</tr>
<tr>
<td>Volume</td>
<td>19 L</td>
</tr>
<tr>
<td>Stator O.D.</td>
<td>19.8 cm</td>
</tr>
<tr>
<td>Rotor O.D.</td>
<td>13.0 cm</td>
</tr>
<tr>
<td>Rotor pole</td>
<td>8</td>
</tr>
<tr>
<td>Stator slot</td>
<td>48</td>
</tr>
<tr>
<td>Motor efficiency</td>
<td>96%</td>
</tr>
</tbody>
</table>

Vector control is widely used in the AC drives through a space vector pulse width modulation (SVPWM) technique. A typical configuration of vector control is shown in Fig. 4 [22]. The principle is to control the \(d\)-axis and \(q\)-axis currents of the motor as per the requirements of the powertrain. This is achieved through an inner control loop (current control) and an outer control loop (speed control), both utilising a PI regulator.
The total electrical power demand can be obtained by:

\[ P_{\text{total}}(i) = P_{\text{EV}}(i) + P_{L}(i) \]  

where \( P_{\text{EV}}(i) \) is the total EV power at time \( i \), and \( P_{L}(i) \) is the load power at time \( i \).

In order to minimize the difference between the actual power demand and the mean value of the power demand, an optimisation model is required.

\[
\min Z(P_{\text{total}}) = \frac{1}{N_d} \sum_{h=1}^{N_d} (P_{\text{total}}(i) - \bar{P}_{\text{mean}})^2
\]

\[
= \frac{1}{N_d} \sum_{h=1}^{N_d} P_{\text{total}}(i)^2 - 1 + \frac{\sum_{h=1}^{N_d} \bar{P}_{\text{mean}}^2}{N_d} \tag{21}
\]

where \( \bar{P}_{\text{mean}} \) is the mean power demand.

Assuming \( n_a \) and \( n_b \) are the number of batteries in different EVs employed for charging (EV1) and discharging (EV2) purposes. The power demand for flexible charging and discharging can be expressed by:

\[
P_{\text{EV1}} = \sum_{i=1}^{n_a} \sum_{j=1}^{N_d} p_j \times \varphi(P_{cij}, h) \times (1 - G_{\text{ODT}});
\]

\[
P_{\text{EV2}} = \sum_{i=1}^{n_b} \sum_{j=1}^{N_d} p_j \times \varphi(P_{dcj}, h) \times (1 - G_{\text{ODT}}); \tag{22}
\]

\[
P_{\text{EV}} = P_{\text{EV1}} - P_{\text{EV2}}; \quad n_v = n_a + n_b \tag{23}
\]

where \( \varphi(P_{cij}, h) \) and \( \varphi(P_{dcj}, h) \) are the probability of a battery charging or discharging at time \( h \), respectively. \( G_{\text{ODT}} \) is the probability of vehicles on the road. \( n_v \) is the total number of EVs.

By substituting Eqs. 22 and 23 into 21, the minimization problem can be developed as.

\[
\min Z = \sum_{h=1}^{N_d} (P_{\text{EV}}(h) + P_{L}(h))^2
\]

\[
= \sum_{h=1}^{N_d} \left( n_a \sum_{j=1}^{N_d} p_j \times \varphi(P_{cij}, h) \times (1 - G_{\text{ODT}}) - n_b \sum_{j=1}^{N_d} p_j \times \varphi(P_{dcj}, h) \times (1 - G_{\text{ODT}}) + P_{L}(h) \right)^2
\]

\[
\text{Subject to} \quad \{ f(h) \geq 0, q(h) \geq 0, \forall t \in [1, N_d] \} \tag{24}
\]

where \( Z \) is the objective function with respect to the optimization problem. \( f(h) \) and \( q(h) \) are the probability of EVs charging/discharging actions at time \( h \). Based on these calculations, EV performance can be evaluated using the real-world operating data.

### III. Test Results Based on Real-World Driving and Charging Cycles

The developed powertrain model is verified by real-world operating data.

#### A. Energy consumption under a daily driving cycle

The test is based on one day operation (06/10/2017) of a Nissan Leaf in Birmingham and its route is shown in Fig. 6.
Fig. 6. The driving route of the EV.

The EV started from point A to B during the period 12:48-13:00, and then went back to A from 13:25 to 13:40. Then it stopped at point C between 18:05 and 18:15. By removing the rest time, the total driving period on the day is presented in Fig. 7(a) with a condensed operating period of 32 minutes. The waveform of the motor torque and acceleration are illustrated in Fig. 7(b) and (c), receptively. During the driving period, the vehicle speed ranges from 0 to 53 mph and the acceleration is generally less than 4m/s², reflecting the road condition in urban Birmingham. The simulation results are presented in Figs. 8-11.

Fig. 8 shows the battery SOC results from simulation model and real tests. The red solid line represents the real test SOC and its tendency is shown in green dash line. The SOC results from the simulation model is presented in solid black. The two curves agree well with each other.

Fig. 7. EV performance. (a) Vehicle speed. (b) Motor torque. (c). The acceleration of the EV.

Fig. 8. Comparison of battery SOC between simulation and real tests.
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Fig. 10. The relationship between the battery SOC and energy consumption.

Fig. 9 demonstrates a relationship between the vehicle speed and battery SOC. The dark solid line indicates the vehicle speed and the red line shows the changing rate of SOC. The average changing rate of SOC is around 0.03. By comparison, the SOC is under 0.008 during the period 00:31:47 to 00:32:14 in the low speed range. It is clear that the energy consumption increases with the vehicle speed. Fig. 10 further confirms the agreement between the battery SOC and energy consumption.

Fig. 11 presents the consumed power and energy during the driving cycle. Both waveforms present similar fluctuations as the battery is the only power source. More specifically, Fig. 11(b) illustrates a comparison of energy delivered by the motor (red solid line) and the battery (blue solid line). The gap between the two is the energy lost in the transmission from the batteries to the motor.

The consumed motor energy and battery energy are given by,

\[ E_{m_{total}} = \sum P_m = 2.802 \text{ kWh} \]
\[ E_{b_{total}} = \sum P_b = 3.718 \text{ kWh} \]
\[ \eta = \frac{E_{m_{total}}}{E_{b_{total}}} = 75.4\% \]  

where \( E_{m_{total}} \) is the consumed motor energy, \( E_{b_{total}} \) is the consumed battery energy, \( P_m \) is the motor output power, \( P_b \) is the battery power and \( \eta \) is the energy efficiency. The efficiency (75.4\%) is much better than that for conventional ICE vehicles (approximately 15\%), suggesting the benefits of adopting EVs in addition to reduced CO\(_2\) emissions.

This EV journal consumes 3.718 kWh for a distance of 27.36 km. The equivalent CO\(_2\) emissions are calculated [23][24] in order to compare between the EV and ICE vehicles, and between different electricity generation technologies. These are tabulated in Table III based on a compact ICE car Volkswagen Golf 2012 [23]. It is clear that the use of EVs can significantly reduce the CO\(_2\) emissions for personal transportation but they are not emission-free. Depending on how electricity is generated, this EV journal would emit equivalent CO\(_2\) of 0.015-1.956 kg. Hydro power is the lowest as it is renewable and low in cost.

Furthermore, an annual consumption is estimated on the same journal for 200 working days per year, as shown in Fig. 12. The amount of CO\(_2\) emissions produced by the EV are no more than 30% of an ICE vehicle. Combined with electricity generation from renewable energy, the environmental benefits of using EVs are significant.
TABLE III COMPARISON OF CO$_2$ EMISSIONS

<table>
<thead>
<tr>
<th>Type of vehicles</th>
<th>Electricity source</th>
<th>CO$_2$ (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE</td>
<td>--</td>
<td>6.68</td>
</tr>
<tr>
<td>EV</td>
<td>Conventional fuel</td>
<td>1.96</td>
</tr>
<tr>
<td></td>
<td>Mixed (fuel and renewable)</td>
<td>1.32</td>
</tr>
<tr>
<td></td>
<td>Solar</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>Wind</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>Hydro</td>
<td>0.015</td>
</tr>
</tbody>
</table>

Fig. 12. Comparison of annual CO$_2$ emissions.

B. Power dispatch under a daily charging cycle

In order to optimize the power dispatch, a number of similar EVs are involved based on the previous demand power, number of the vehicles, and probability of EVs connecting to the grid. The load profiles for different numbers of EVs are obtained and presented in Fig. 13.

Fig. 13. Optimized and original power demand profiles.

Under this condition, the load demand in 24 hours is based on the European Bioenergy Research Institute (EBRI) building in Birmingham, which is equipped with several charging stations for Nissan Leaf. Among these is one vehicle-to-grid (V2G) charging station, which is used in this study. The demand is obtained in 48 intervals (0.5 hour each). The EV’s V2G performance is evaluated according to the different number of EVs (1-4) connected to the grid. The probability of EV connecting to the power system network is derived from the rest time in the previous EV journal. In order to keep the EV operational for daily travels, the maximum energy for V2G operation is limited. In this case, it is 70% of capacity which can be used for V2G grid support. From Fig. 13, the fluctuations of load demand are minimized by increasing the number of EVs for flexible charging and discharging operation. The optimized load demand would be much closer to the idealized mean load. However, as the EVs do not support the power network during driving periods, some fluctuations are not minimized in the figure.

IV. CONCLUSIONS

In this paper, an analytical model of an EV powertrain has been presented, including both mechanical and electrical sub-systems. The system dynamic responses to changes in vehicle speed, acceleration, machine speed and torque have been studied in detail. An online AEKF SOC method is developed for battery management. The analytical model of the EV powertrain has been validated by simulation and actual test results from the test driving cycles. EV power and energy consumption based on the real driving tests can also be obtained to estimate their impact on the environments. Finally, a flexible power dispatch can be achieved by utilizing more EVs under controlled charging and discharging conditions. Therefore, EVs can be scheduled to support the power grid through V2G operation.

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