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Performance Analysis of Electrical Vehicles Batteries using Kalman Filter

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Abstract. The lithium-ion (Li-ion) battery plays a crucial role in the performance of electric vehicles, owing to its unique properties and compact size. To ensure the prolonged lifespan of these batteries, it is imperative for users to exercise additional precautions. The variable load torque applied to the Permanent Magnet Synchronous Motor (PMSM) drive, influenced by diverse road conditions, adds complexity to the scenario. Assessing the State of Charge (SoC) of the Li-ion battery proves to be a significant challenge, given the multitude of electrical sensors and mechanical components involved in the operation of electric vehicles (EVs). In such instances, the SoC may be subject to noisy measurements, leading to performance degradation of the battery over time. This paper proposes the utilization of the Kalman filter to estimate the actual SoC from the noisy measurements, relying on indirect measurements as a basis for improved accuracy.

1 Introduction

In the modern automotive landscape, advancements in electric and hybrid vehicles are driven by the interplay between Battery Management Systems (BMS) ensuring safe and efficient battery operation, and Vehicle Control Units (VCU) providing intelligent control over the entire powertrain. [1-3]. The BMS is responsible for monitoring and managing the State-of-Charge (SoC), State-of-Health (SoH), State-of-Function (SoF), and other parameters of the battery. It also provides protection against overcharging, over discharging, overcurrent, short circuiting, and other faults. The VCU is responsible for controlling the powertrain, including motor speed, torque, regenerative braking, and other functions. In contrast, a VCU serves as the brains of the car, managing the drivetrain, brakes and steering, among other things, to improve efficiency, performance and safety. These systems work together to facilitate the shift to greener, more sustainable modes of transportation, which makes them crucial parts of the development of vehicle of the future[4-6-. In general, the main components of the EV illustrated in Figure 1,

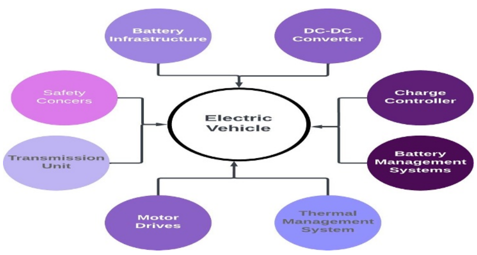

Fig. 1: Components of EV

The majority of the functions of motor drives is to manage the electric motor by utilizing power electronic switches to regulate power delivery. They interpret the commands that obtain from the vehicle control unit into the appropriate signals for the motor. Instead of a complicated transmission, the majority of electric vehicles (EVs) include a single-speed reduction gear. For best results, the gear exclusively regulates the motor's rotation speed in relation to the wheels [7-10]. However, there are two ways to understand the communication that occurs between motor drives and BMS:

(a) The motor drives may receive information from the BMS regarding the condition and current capacity of the battery, enabling them to modify power delivery as necessary.

(b) On the other hand, electric motor drives may report the motor's current demand to the BMS, which may affect the battery health calculations.

The complex configuration or model of the Battery Management System is connected to several sensors, motor drives, road conditions, and driving patterns. This can be further discussed technically below:

(a) Battery Management System (BMS) relies on sensor data to assess battery status and optimize performance.

(b) Sensors are susceptible to noise from: Motor drives (electrical fluctuations caused by motor operation) and Road conditions (vibrations)

(c) This noise corrupts the data, making it difficult to accurately deter- mine: Battery current draw (how much current the battery is supplying) Battery health (remaining capacity, degradation).

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To solve this problem, an effective filtering technique like the Kalman filter is used. Battery life assessment becomes possible when the noisy sensor data from motor drives are effectively separated from the underlying SOC signal by the Kalman filter [11,12].

2 EV System

In Electric Vehicles (EVs), accurately gauging the remaining battery capacity, or State-of-Charge (SOC), is essential. The Kalman filter is a powerful technique employed in EV systems to estimate SOC by combining a battery model with real-time measurements. Kalman filter is used for SOC estimation in EVs are:

(a) System Model: The Kalman filter leverages a mathematical model that captures the battery's discharge dynamics. This model is often represented by a state transition matrix (A) that describes how the SOC changes over time. Factors like current discharge and aging can be incorporated into this model.

(b) State Variable: The state variable in this case is the battery's SOC, typically expressed as a percentage of its full capacity.

(c) Measurements: The Kalman filter integrates real-time measurements from the battery, such as:

Current: The current flowing into or out of the battery (positive for charging, negative for discharging) is a crucial measurement for estimating SOC changes.

Voltage: Battery voltage can also be used, but its relationship to SOC is non-linear and temperature-dependent. It might be incorporated alongside current or used for periodic corrections.

Temperature: Temperature significantly affects battery capacity. Some Kalman filter implementations might directly include temperature as

a measurement or use it to adjust the battery model.

(d) Process Noise (W_k): This represents uncertainties in the battery model, such as inaccuracies in capturing aging effects or unexpected variations in discharge behaviour.

(e) Measurement Noise (R_k): This signifies uncertainties associated with the sensor measurements, like current sensor noise or limitations in voltage-to-SOC conversion accuracy.

Overall, the Kalman filter is a valuable tool for EV systems to estimate battery SOC, contributing to optimal battery management, improved driving range prediction, and overall EV performance.

3 Kalman Filter Algorithm

In Battery Management Systems (BMS), Kalman filtering is an efficient method for estimating an electric vehicle's (EV) remaining battery life. The Kalman Filter Algorithm The system and measurement equations, as well as the related noise properties, are sent into the Kalman filter as shown in Fig. 2.

It completes the following two steps iterative:

(a) Prediction: Using the system model and the previous estimate, it forecasts the battery's state of charge (SOC) for the next time step.

(b) Update: Using the battery's actual readings and the noise levels that correspond with them, it adjusts the prediction.

Advantages of the Kalman Filter:

(i) When using Kalman filtering instead of just voltage measurements, the SOC can be estimated with more accuracy.

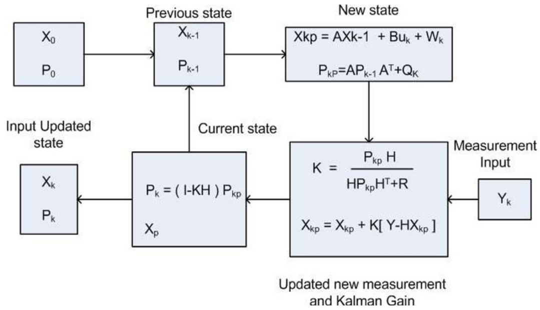

Fig .2: Process of Kalman Filter

(ii) It produces a more reliable estimate by considering measurement noise and battery model uncertainties into consideration.

The Kalman filter is a mathematical algorithm used for estimating the state of a dynamic system from a series of noisy measurements. In the context of estimating the state of charge (SoC) in batteries, the Kalman filter can be employed to provide a more accurate prediction of the current SoC based on the available measurements. The Kalman filter process represented in the block diagram are:

(a) Initial State (X_0): This represents the initial estimated state of the system. It includes the battery's initial current, voltage and temperature.

(b) Previous State (X_{k-1}): This block represents the plane's estimated state from the previous time step. It includes its current, voltage and temperature at that time.

(c) New State (Predicted) (X_{kp}): In this step, the filter predicts the battery's new state based on the previous state and a process model that factors in the system's dynamics, represented by the state transition matrix A and the control input matrix B. Process noise W_k is incorporated here to account for uncertainties in the system's behaviour. The equation for this step is:

$$X_{kp} = AX_{k-1} + Bu_k + W_k \tag{1}$$

(d) Calculate New State Covariance (P_{kp}): This step calculates the uncertainty associated with the predicted new state. It considers the previous state's covariance matrix Pk−1and the process noise covariance matrix Q_k. The equation for this step is:

$$P_{kp} = AP_{k-1}A^T + Q_k \tag{2}$$

(e) Update with new measurement (Y_k): This block signifies a new measurement, likely from a sensor, that provides information about the battery's state.

$$Y_k = CY_{km} + Z_m \tag{3}$$

(f) Kalman Gain (K): The Kalman gain K is computed in this block. It determines how much weightage to give to the new measurement based on the certainty in the predicted state (represented by the predicted state covariance matrix Pkp) and the certainty in the measurement (rep- resented by the measurement noise covariance matrix R). The equation for this step is:

$$K = P_{kp}H/ (HP_{kp}HT + R \quad (4)$$

(g) Update state estimate (X_k): This step refines the predicted state estimate (X_k)by incorporating the new measurement (Yk) and the Kalman gain (K). The equation for this step is:

$$X_k= X_{kp} + K(Y - HX_{kp}) \quad (5)$$

(h) Update state covariance (Pk): This step calculates the uncertainty associated with the updated state estimate, considering the predicted state covariance (Pkp), the Kalman gain (K), and the measurement noise covariance matrix (R). The equation for this step is:

$$P_k = (I - KH)P_{kp} \quad (6)$$

List of Symbols
H: Measurement Matrix
I: Identity Matrix
K: Kalman Gain
P: Process Covariance Matrix
Q: Process Noise Covariance Matrix
R: Sensor Noise Covariance Matrix
u: Control Variable Matrix
W: Predicted State Noise Matrix
X: State Matrix
Y: Measurement of the State

4 Results and Discussion

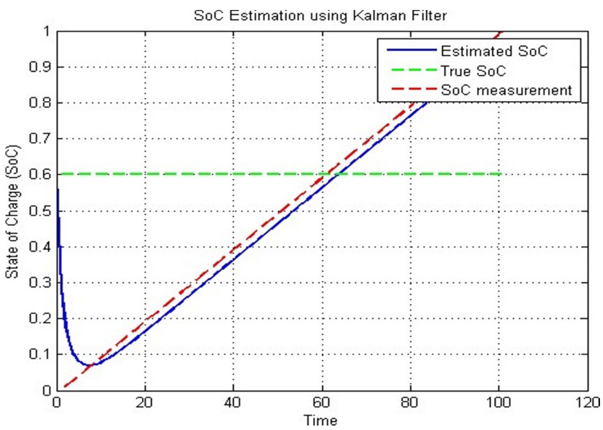

Fig. 3. State of Charge

The state of charge of the battery is s shown in Fig. 3.
Blue Line (Estimated SoC): This line represents the Kalman filter's estimate of the battery's state of charge (SoC) at each point in time. It's constantly being updated based on the system model and the received measurements.
Green Line (True SoC): This line shows the actual state of charge of the battery, which is the ideal value we want to know.
Red Line (SOC Measurement): This line represents the actual measurements obtained from the battery, such as its voltage and current. These measurements are often noisy and contain some inaccuracies.

The closer the blue line (estimated SoC) is to the green line (true SoC), the more accurate the Kalman filter's estimation is in the graph we have provided, it seems the filter is tracking the true SoC quite well.

5 Conclusion

In conclusion, this study investigated the impact of driving load conditions on permanent magnet synchronous motor (PMSM) load torque and its influence on battery life. The Kalman filter algorithm was successfully implemented to estimate the battery's state of charge (SoC) by mitigating noise from sensormeasurements. This approach facilitated the acquisition of more accurate SoC data, enabling a clearer understanding of the relationship between driv- ing loads and battery life. The findings demonstrate the Kalman filter's effectiveness in battery management systems for electric vehicles, potentially leading to improved battery health monitoring and optimized driving range predictions.

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