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An Overview of Lithium-Ion Battery Dynamics for Autonomous Electric Vehicles: A MATLAB Simulation Model

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Abstract

This paper presents a detailed simulation model designed for autonomous electric vehicles (AEVs) powered by lithium-ion batteries. It provides insights into the input parameters used in the model and the recuperation of braking energy in AEVs. In addition, the paper offers a thorough analysis of the dynamic characteristics of lithium-ion batteries through simulations of standardized driving cycles, including urban and highway drive cycles. These results are expected to facilitate the progress of AEV battery technology development and promote the creation of more sustainable and efficient self-driving vehicles.

Subject Areas

Electric Engineering, Network Modeling, and Simulation

Keywords

Autonomous Electric Vehicles, Battery Management Systems (BMS), Lithium-Ion Batteries, Dynamic Mode Simulation, EV Drive, Drive Cycles, Self-Driving Vehicles

1. Introduction

Despite the recognized issues [1] and the emergence of alternative solutions [2], there is a strong upward trend in the production of batteries for Autonomous Electric Vehicles (AEVs) [3]. Market growth has reduced production costs and increased investment in the development of AEVs [4] [5]. The main solutions to the issues of autonomy and extended travel range include designing batteries with higher energy density [6], reducing battery weight, and optimizing dynamic charging and discharging modes [7].

Lithium-Ion batteries have several advantages compared to other battery types [8], including higher efficiency and energy density, increased nominal voltages, lower specific weight, longer lifetime, faster and more efficient charging, smaller size, no maintenance requirements, and greater resistance to external conditions [9] [10] [11].

However, Lithium-Ion batteries also have some drawbacks, such as the need to avoid complete discharge, which may shorten their lifespan. Discharging them with high currents is also not recommended due to the risk of damage. These limitations can be addressed by using electronic circuits to manage the battery's charging and discharging processes [8].

AEVs have the potential to reduce transportation costs and petroleum usage since they have no tailpipe emissions, making them environmentally friendly. The battery technology improvements have also gained increased development, especially in their range, making them a viable option for long-distance travel. Although they are generally more expensive than gasoline-powered vehicles, the cost of ownership is lower due to battery durability, lower maintenance, and fuel costs as shown in **Figure 1**. They are in an optimal position to significantly reduce petroleum consumption, leading to lower greenhouse gas emissions and better air quality. As their battery technology improves and production volumes increase, AEVs will become more affordable and accessible [4].

This paper observes the transient behavior of Lithium-Ion batteries in various modes of operation and analyzes the impact of charging and discharging on AEV operational parameters. The outcomes of this study are anticipated to promote the advancement of AEV technology, particularly in optimizing battery efficiency and stimulating the fabrication of more environmentally friendly and

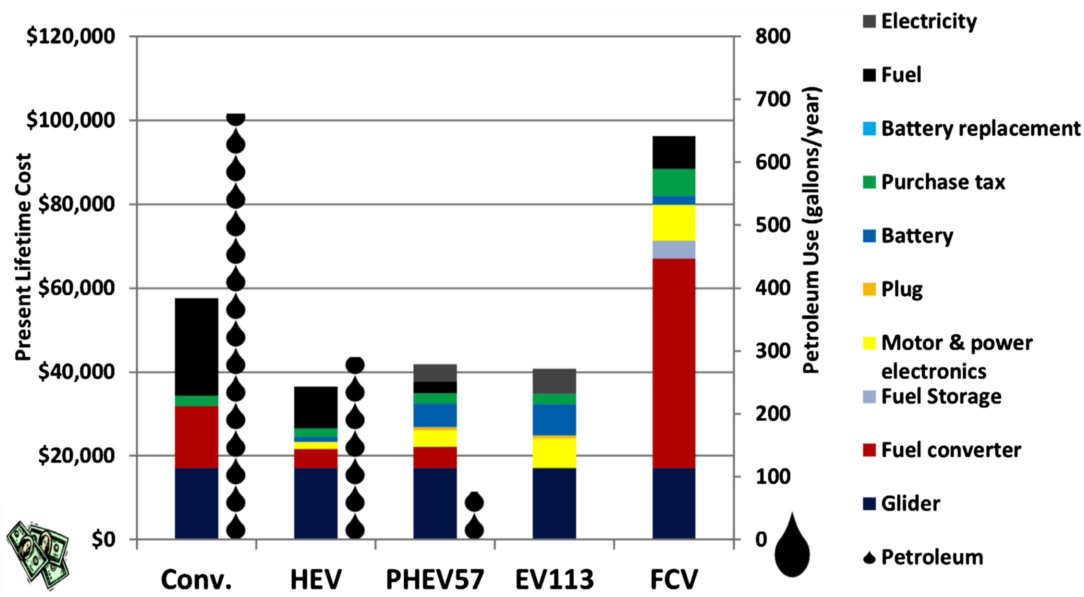

Figure 1. Present cost and petroleum usage chart.

effective vehicles.

Lithium-ion batteries are the primary power source for autonomous electric vehicles, and the state of charge and power output of these batteries are critical parameters for their effective operation. In a previous study, a simulation model was proposed for lithium-ion batteries in autonomous electric vehicles, which provides insights into these critical parameters [12]. Before this proposal, research was conducted on the comparative analysis of various lithium-ion battery models for autonomous electric vehicles [13], analyzing their accuracy in predicting battery behavior under different driving conditions. Researchers found that models that consider the thermal behavior of batteries tend to be more accurate.

Further work was conducted in this field presenting a control-oriented model for a lithium-ion battery pack used in autonomous electric vehicles. The model focuses on developing a battery charging and discharging strategy to optimize its performance [14].

One significant acknowledgment in the development of AEVs has indicated that battery management systems play a crucial role in the effective operation of lithium-ion batteries used in AEVs [15]. Researchers have proposed a battery management system design that includes strategies for battery balancing and thermal management to ensure the battery's longevity [16]. Thermal management is also essential for the effective operation of lithium-ion batteries in electric vehicles, including autonomous electric vehicles. The use of phase change materials for battery thermal management has been reviewed and extensively investigated, which can improve the battery's performance and safety [17].

Hybrid modeling approaches combining physical and empirical models have been proposed to improve the accuracy of lithium-ion battery performance prediction [18]. Researchers have presented a hybrid modeling approach for lithium-ion batteries used in autonomous electric vehicles, which can help to optimize battery performance. Several studies also focused on optimizing battery capacity and energy efficiency for lithium-ion batteries used in electric vehicles, including autonomous electric vehicles [19]. Simulation models were developed to effectively optimize the battery design for these applications. An overview of the thermal management strategies for lithium-ion batteries used in electric vehicles, including autonomous electric vehicles, has been discussed in earlier studies, where the impact of thermal management on battery performance and safety is theoretically emphasized.

Due to various challenges, the AEV may face in the future, researchers have presented a multi-objective optimal design for a lithium-ion battery, which can be applied to autonomous electric vehicles. The design aims to maximize the battery's energy density while minimizing its cost [20].

2. Lithium-Ion Battery—Model Development

This paper employs the MATLAB software to design and verify a general model of a Lithium-Ion battery based on Shepherd's model for simulating various driving modes of Autonomous Electric Vehicle (AEV) drives and battery packs (as shown in **Figure 2**). The model is structured as a voltage source controller, with its output determined by the current state of charge (SoC) of the battery. The purpose of this approach is to obtain input parameters for the battery model (as depicted in **Figure 3**) from the manufacturer's catalog data using a simple process. The model includes several functions that depend on the battery voltage and modes of operation. The aim of this research is to advance the development of more efficient and sustainable AEVs [21].

The discharge profile of Lithium-Ion batteries is presented in **Figure 4** and can be segregated into three distinctive regions. The initial region, also referred to as the exponential regime, is distinguished by the battery voltage surpassing its nominal value. The battery operates within this regime during the phase of establishing a stable discharge current following a no-load battery mode. During the discharge mode in the nominal battery operating area, there is a slight voltage change. As the battery's nominal capacity is discharged, it enters the third operation area where the voltage rapidly decreases.

The battery discharge curve, depicted in **Figure 4** as a red line, is nonlinear and follows the Shepherd model's Equation (1) during the charging current's

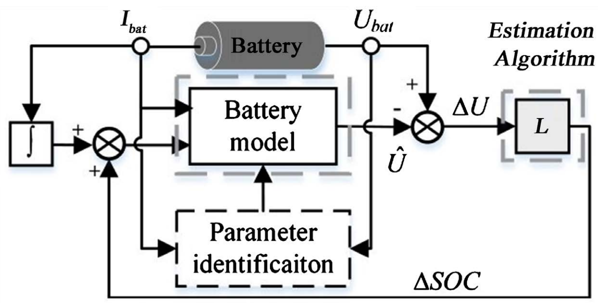

Figure 2. The Lithium-Ion battery model-based State of Charge (SoC).

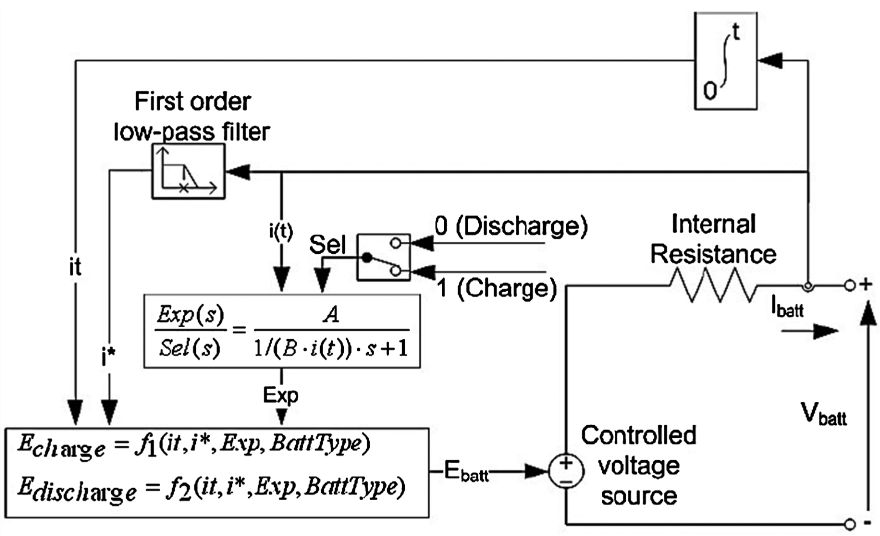

Figure 3. The battery model—block diagram (MATLAB-Simulink).

positive state ($i^* > 0$).

$$f_1\left(i_t, i^*, i\right) = E_0 - K\frac{Q}{Q - i_t}\cdot i^* - K\frac{Q}{Q - i_t}\cdot i_t + A\cdot\exp\left(-B\cdot i_t\right) \tag{1}$$

$$f_2\left(i_t, i^*, i\right) = E_0 - K\frac{Q}{Q - i_t}\cdot i^* - K\frac{Q}{Q - i_t}\cdot i_t + A\cdot\exp\left(-B\cdot i_t\right) \tag{2}$$

where: E_0—Constant voltage (V), K—Polarization resistance (Ω), i^*—Low frequency current dynamics (A), i—Battery current (A), i_t—Extracted capacity (Ah), Q—Maximum battery capacity (Ah), A—Exponential voltage (V), B—Exponential capacity (Ah^{-1}). The second component of Equation (1) is the polarization voltage, which is the result of multiplying the polarization resistance and the battery current. This term explains the behavior of the battery when it is not under load.

The discharge characteristics at various currents are shown in **Figure 5**, demonstrating variations in behavior [21].

The battery's charging characteristic, graphically represented in **Figure 5** and mathematically formulated in Equation (2), exhibits an inverted profile with respect to the discharge feature. The charging process commences from an empty

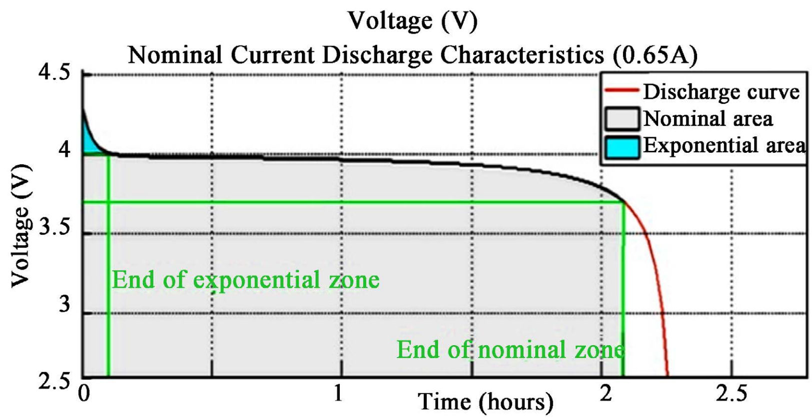

Figure 4. Discharge of the Lithium-Ion battery at nominal discharge current.

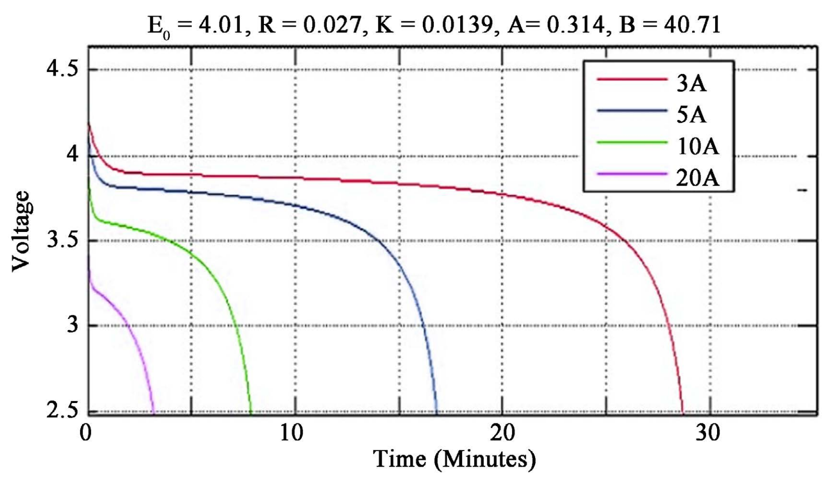

Figure 5. Battery discharged at various currents (Nominal Discharge Current = 0.65 A).

battery condition and rapidly builds up the nominal voltage before continuing at a constant voltage level. Finally, it enters an exponential stage, where the voltage is restored to the no-load value. Since the charging current has an opposing polarity ($i^* < 0$), the polarization resistance varies, resulting in a slightly different voltage function. This paper disregards the impact of temperature on the Lithium-Ion battery's performance [21]. Considering the dynamic behavior of the Lithium-Ion battery, especially during the exponential region and rapid capacity loss phase, it is crucial to utilize advanced power electronic systems to prevent overheating and damage. To ensure an accurate analysis of an autonomous electric vehicle's drive, it is essential to take into account the various assumptions presented in the model [22]. These assumptions include the constant internal resistance of the battery regardless of the mode of operation (charging or discharging) and the magnitude of the current. The model assumes the hysteresis effect of the battery voltage curve to be negligible, and the battery capacity to remain unchanged with respect to the charging current. The model neglects the temperature dependencies of battery parameters and the possibility of self-discharge, while assuming the battery to have no memory effect. As the simulations provide only discrete states of the battery, the model with concentrated parameters imposes certain restrictions: the battery voltage and capacity cannot be negative, and the voltage reaches zero at complete discharge. Moreover, when overcharged, the battery's maximum state of charge (SOC) may exceed 100% [22].

In order to verify the generic battery model, input parameters from the Mitsubishi xAuto Electric Vehicle were selected [23]. The base of the battery pack within the model was a single battery cell with a nominal voltage of 3.75 V. The MATLAB program was then utilized to generate discharge curves for various currents, as depicted in **Figure 6**. Additionally, the parameters obtained from the manufacturer's catalog using the method previously described can also be observed in **Figure 5**.

Mitsubishi Electric has created xAuto EV technology, prioritizing safety, and convenience (as depicted in **Figure 7**). This self-sensing driving technology combines peripheral-sensing technologies with network-based driving technology to enable autonomous driving in various road conditions, including those with low visibility. Field tests have confirmed the effectiveness of this autonomous driving technology. Mitsubishi Electric's future plans include developing high-accuracy 3D mapping and establishing a global wireless network for centimeter-level positioning compatible with CLAS broadcasting from the Quasi-Zenith Satellite System (QZSS) [23]. Ongoing testing aims to improve the self-sensing driving technology further, focusing on collision avoidance at crosswalks and forward-monitoring camera technology based on vision.

3. Parameters Setting for AEV Drive

This paper compares the performance of autonomous electric vehicles (AEVs) based on their ability to cover a predetermined distance from a fully charged

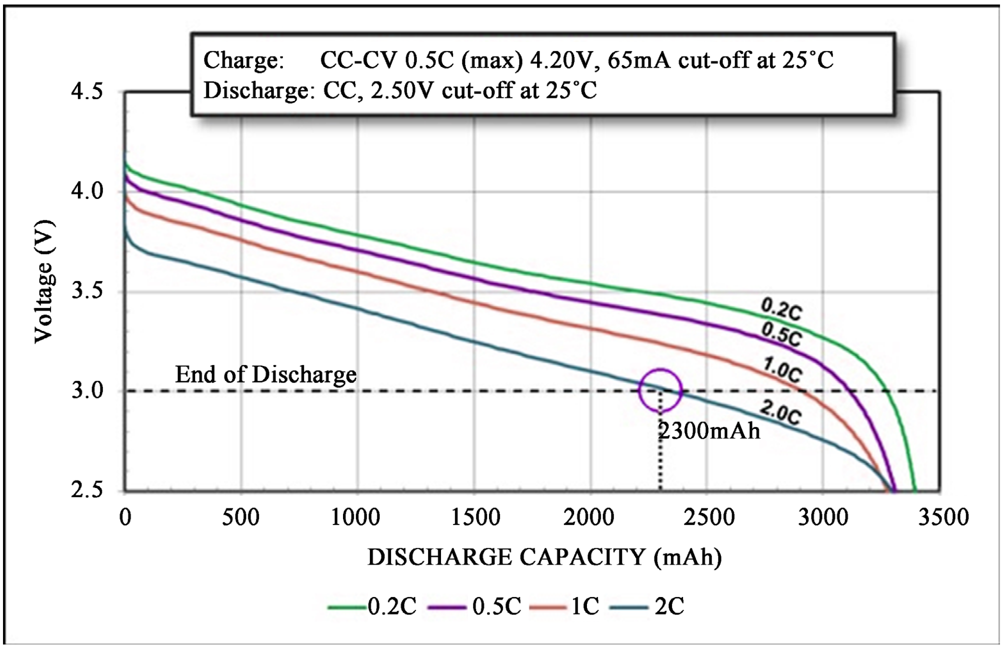

Figure 6. Lithium-ion battery standard discharge curve (different characteristic areas).

Figure 7. Mitsubishi xAuto autonomous-driving vehicle.

battery under specific driving conditions. Two standardized driving cycles are used (refer to Figure 8 and Figure 9):

1) the Urban Dynamometer Driving Schedule (UDDS), which covers a distance of 12 km in 1380 seconds (23 minutes) with an average speed of 36.6 km/h.

2) The simulation is then verified using the combined UDDS (10 km) and EPA Highway Fuel Economy Test (HWFET) (30 km) driving cycles.

The initial parameters are set based on the UDDS driving cycle, and the combined UDDS (10 km) and HWFET (30 km) driving cycles are used for simulation verification of the model [24].

Defining all parameters that affect the AEV's performance is necessary to calculate the battery dynamics through simulation. The energy required to power

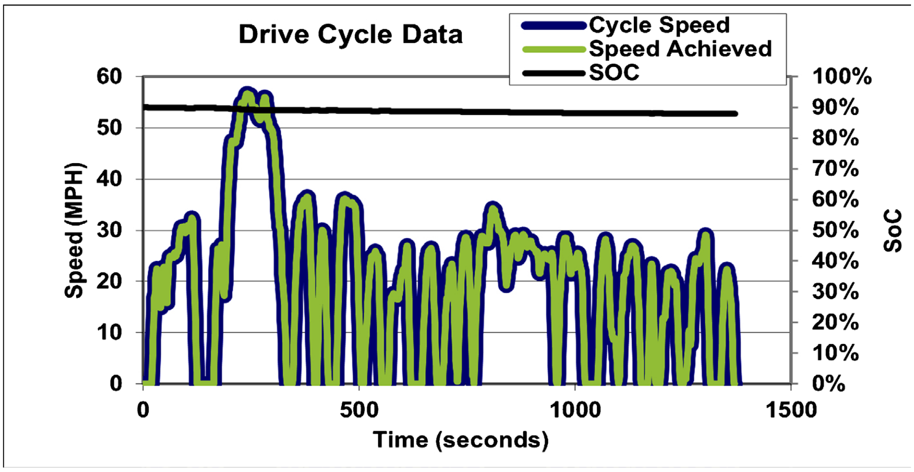

Figure 8. Urban dynamometer driving cycles UDDS.

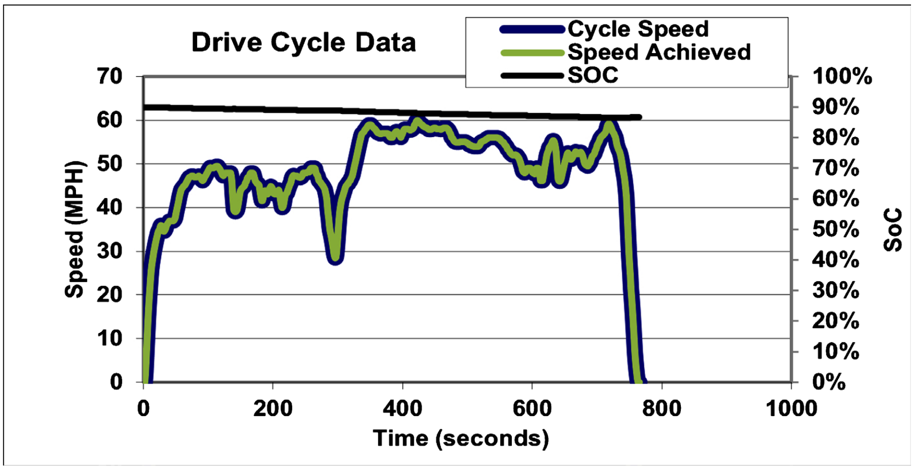

Figure 9. EPA highway fuel economy test HWFET.

the AEV's drive is determined by the driving mode and basic vehicle parameters [25] [26] [27]. This energy is transmitted as an electrical load to the battery through the electric drive and is discharged during acceleration and driving while being charged during braking energy recovery. However, this paper simplifies the analysis by ignoring energy losses within the AEV, which can be as high as 20% under real-world conditions. The calculations also assume a standard route and do not consider changes in vehicle inclination, such as driving uphill or downhill [24].

According to [28], the total mechanical power can be obtained by adding the product of the total resistance force acting on the vehicle while in motion and its corresponding velocity at a specific moment in time.

$$P_{mechinal} = \sum F \cdot v \tag{3}$$

Three components contribute to the total resistance force experienced by a moving vehicle as per [28]: rolling resistance, air resistance, and gradient resistance. These individual components are modeled in Simulink and then integrated into a common subsystem referred to as "UDDS load". **Figure 10** depicts the structure of this subsystem [24]. The drag coefficient (C: 0.0425) and frontal area (A) values used in this paper are sourced from the base vehicle model, the Mitsubishi xAuto EV. The MATLAB model of the AEV utilizes the same values for air density (1.2 kg/m^3), rolling friction coefficient (0.013), and transmission coefficient (1.03) as reported in [23]. The selected driving cycle determines the vehicle speed used as input into the MATLAB model, and acceleration is obtained from the vehicle speed.

The Simulink model is designed to simulate the performance of Autonomous Electric Vehicles (AEVs) under the Urban Dynamometer Driving Schedule (UDDS) and the Highway Fuel Economy Test (HWFET) driving cycles.

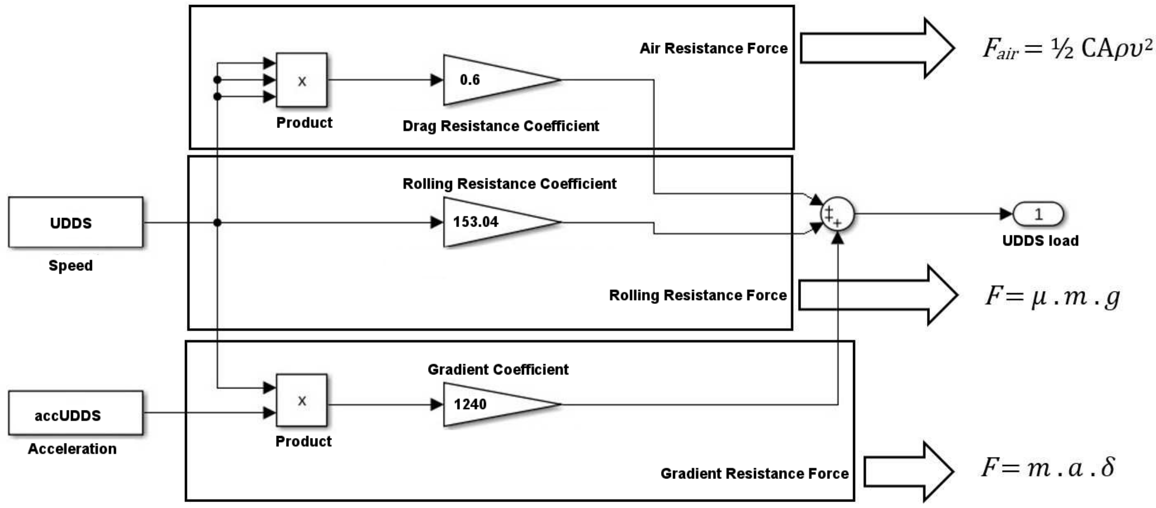

Figure 10. UDDS simulation load block.

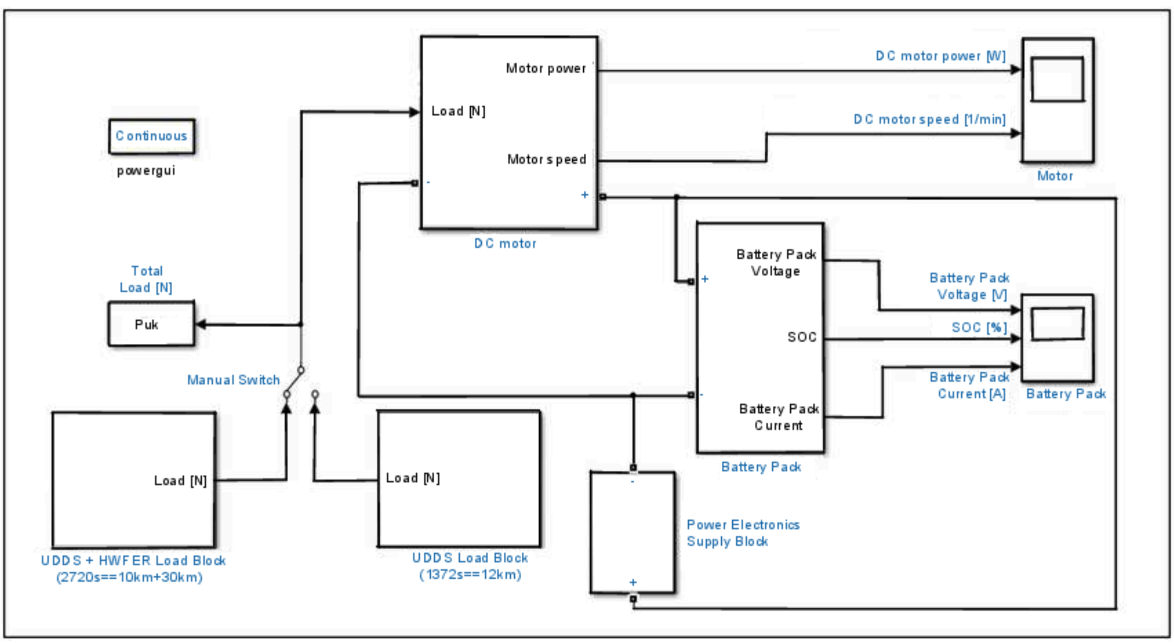

Figure 11. The UDDS and HWFET MATLAB-Simulink Mode.

The mechanical load on the DC motor driving the AEV is calculated by multiplying the opposing force to vehicle movement, as described in [3], with the corresponding speed. This generates a function that characterizes the mechanical load on the motor. The DC motor block's output, which represents the electric energy demand supplied by the battery pack, is depicted in **Figure 11**. The model is based on the xAuto vehicle, which employs a battery pack with a nominal voltage of 330 V. The battery pack comprises 11 modules connected in series, with 8 battery cells in parallel, each with a nominal voltage of 3.75 V. The battery pack model is shown in **Figure 12**.

The power variations required for the AEV drive during the UDDC drive cycle are illustrated in **Figure 13**. The DC motor's power rating is determined by selecting the nearest standard power value that is greater than the highest calculated power value.

At 196 s, the maximum power of 29.2 kW is observed, leading to the selection of a 30 kW DC motor power rating for the AEV drive [24]. The diagram in **Figure 11** also displays intervals of negative power during deceleration, indicating

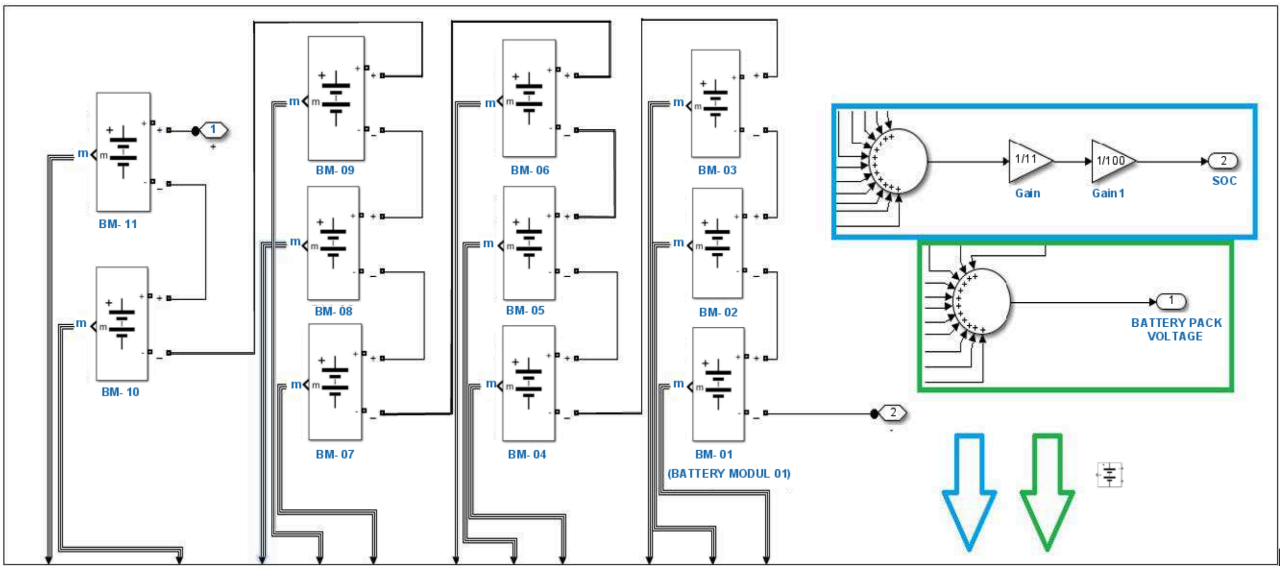

Figure 12. The battery pack model.

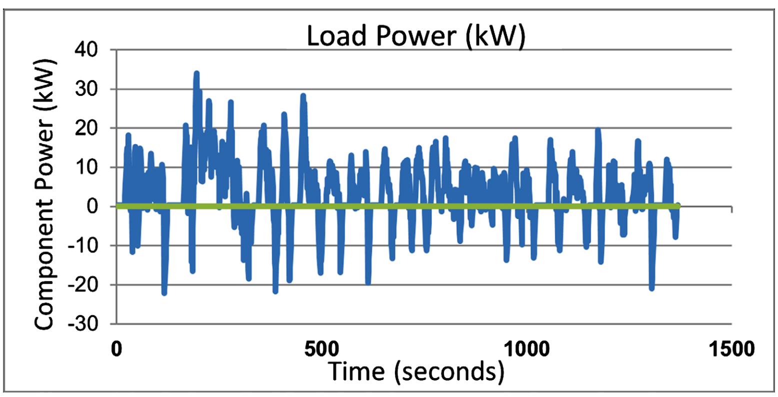

Figure 13. Display of the necessary power during UDDS driving cycle.

the process of regenerative braking, where energy flows from the DC motor block to the battery pack. To calculate the energy required for the AEV drive during the drive cycle, the power function is integrated over time. To determine the battery pack capacity required to supply the energy demand at a specific voltage, the following equation is utilized:

$$C = \frac{W}{3600 \cdot U} \tag{4}$$

The battery pack capacity (C) in Ah is determined using the equation: $C = (W/U) \times 1000$. To calculate the total electrical energy (W) required for the driving cycles, the power function is integrated over time. The total energy required for the simulated driving cycle is found to be 40.1 MJ. However, since Lithium-Ion batteries operate in the capacity range of 25% to 95% for safe use, only 70% of the theoretical capacity is available. Therefore, the calculated total energy value needs to be divided by 0.7 to obtain the correct values [24]. Based on this, the theoretical battery capacity required is approximately 47 Ah.

4. Discussion of Results

To validate the AEV model, the relevant components can be parameterized based on the xAuto EV model [23], and the remaining components of the drive system can be adjusted to meet the requirements of the UDDC drive cycle.

The first step in verifying the AEV model is to confirm that it can cover the driving distance required by the UDDC drive cycle, as shown in **Figure 14** which displays the dynamic characteristics of the battery pack under loads induced by UDDS driving cycles. The DC motor block is responsible for providing

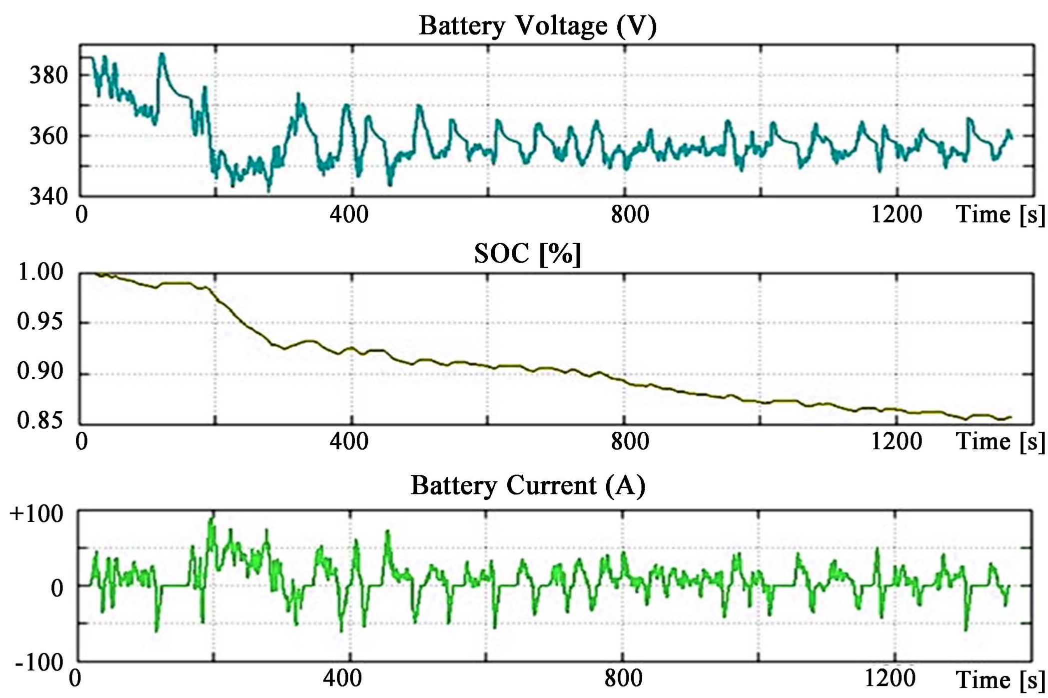

Figure 14. The dynamics of UDDC battery pack drive cycle.

the AEV's speed and power output, and its performance during the UDDC drive cycle is depicted in Figure 15. The green line intervals in the figure indicate periods when the battery is discharging, while purple marks the periods when braking energy is being recuperated. The motor power during acceleration ranges from 70% to 95%, accounting for about 20% of the entire drive cycle [29] [30].

These intervals result in the largest discharge current, putting maximum load on the battery (Figure 13). When cruising, the motor power ranges from 30% to 40%, representing approximately 55% of the drive cycle [25]. The battery discharge current during these periods is almost half as much, and battery stress is reduced. However, since the discharge duration is longer, the SOC changes more intensely, as shown in the diagram in Figure 15.

The simulation's second phase involves testing the model's performance on a combined driving cycle comprising 10 km of UDDC followed by 30 km of HWFET, which takes a total of 3760 seconds. The UDDC drive cycle lasts for 1370 seconds (covering 10 km), and the HWFET cycle lasts for 1350 seconds (covering 30 km), with the vehicle reaching its destination at 2720 seconds. The battery is charged for 1040 seconds with a constant current of 50 A once the vehicle arrives. Figure 17 shows the battery's dynamic characteristics, including SOC, voltage, and current, during the UDDS + HWFET drive cycle, while Figure 16 shows the power and engine speed. The analysis reveals that the vehicle's

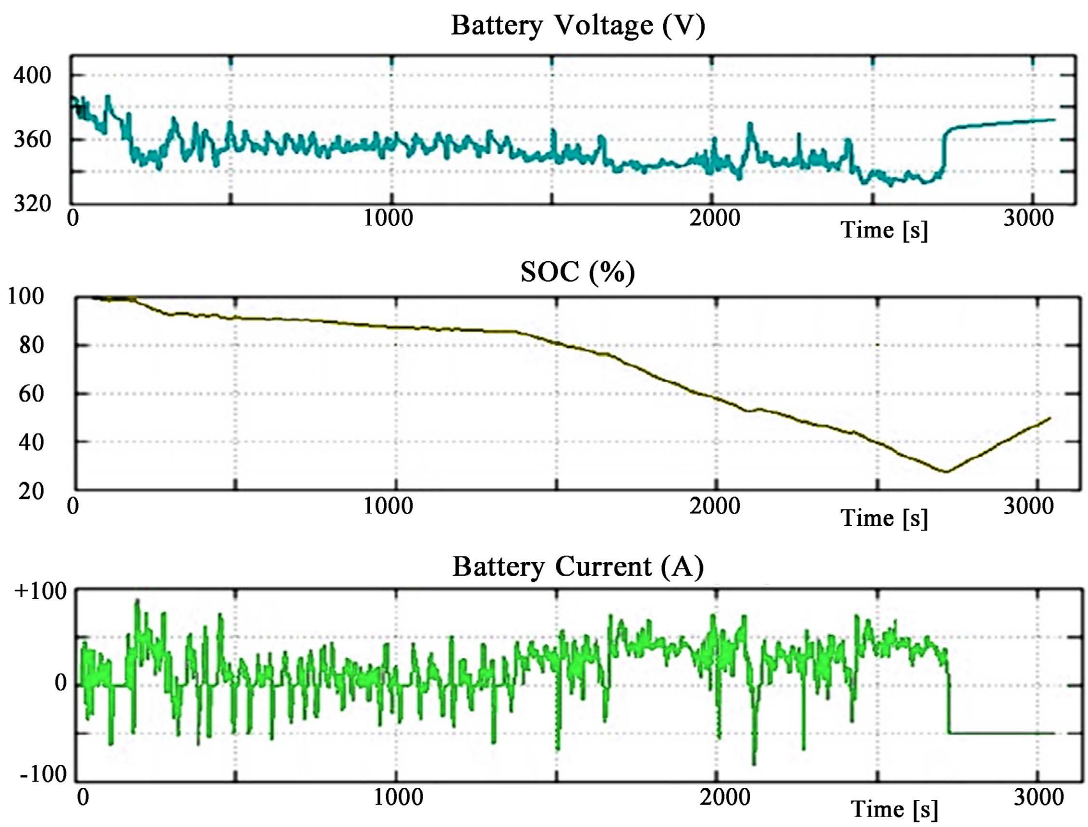

Figure 15. The dynamics of UDDC + HWFET battery pack drive cycle.

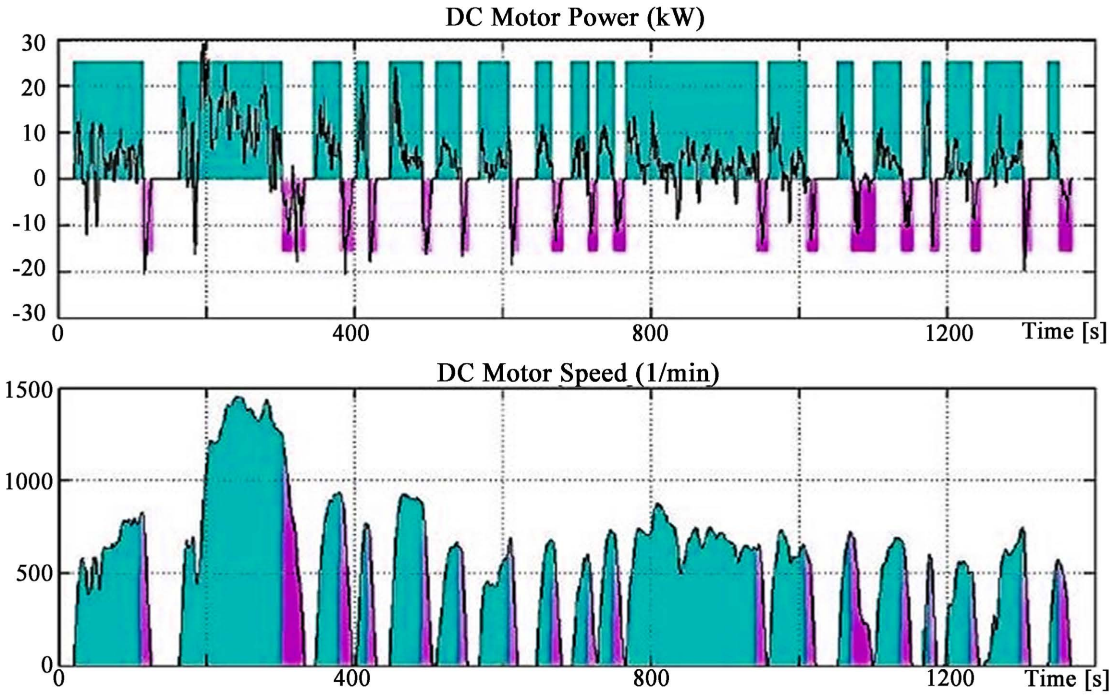

Figure 16. DC motor speed and power for UDDC drive cycle.

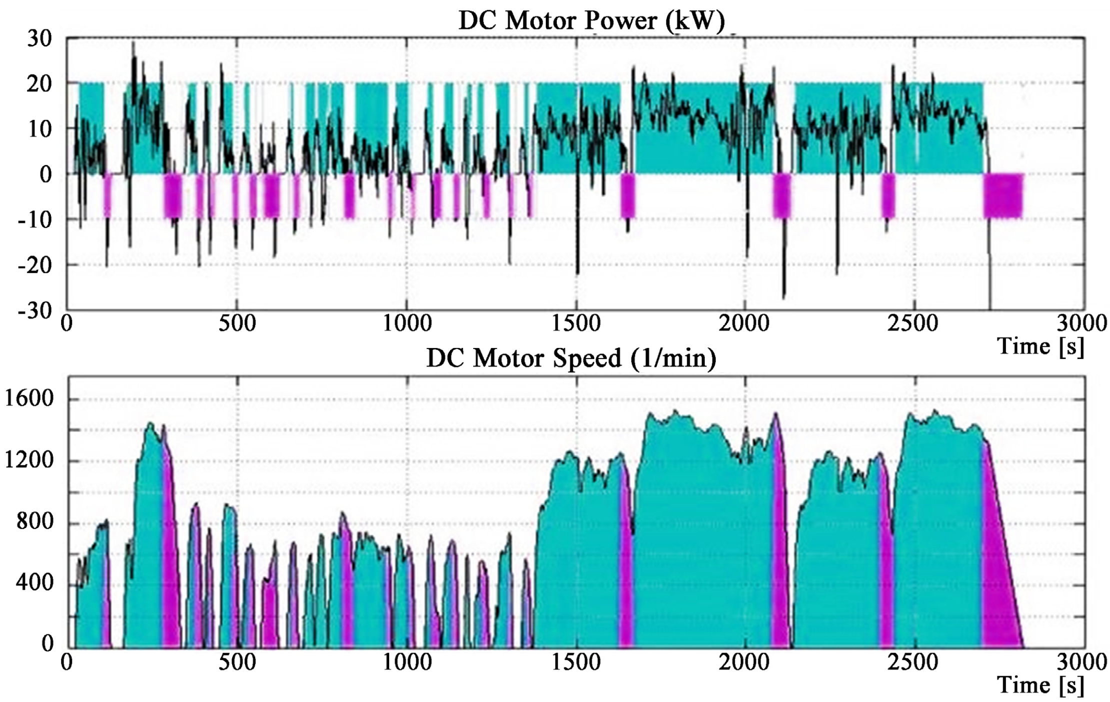

Figure 17. DC motor speed and power for UDDC + HWFET.

frequent stops during the UDDC drive cycle result in energy recovery, leading to a slower decrease in SOC. However, the HWFET cycle causes a significant increase in battery discharge current with minimal energy recovery, leading to SOC decreasing twice as fast. The battery pack is not discharged below 25% at the end of the cycle, as intended.

5. Conclusion

This paper utilized MATLAB-Simulink to parameterize the drive of an Autonomous Electric Vehicle (AEV) and studied the dynamic characteristics of its Lithium-Ion battery during different charge and discharge scenarios. The process of modeling an AEV, selecting battery parameters, and calculating the required power for the drive cycle was presented, along with model simplification and limitations. Future research opportunities were also suggested, including incorporating all parameters that describe a realistic AEV to enhance its distance range. Based on simulations and analysis of results, the paper recommends defining the Lithium-Ion battery's boundary areas for operation in an AEV and selecting measuring signals for control electronics.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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