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Simulation of SOC Estimation in an Electric Vehicle

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***Abstract*— This research focuses on the simulation of an electric vehicle (EV) and its battery's state-of-charge (SOC) estimation using MATLAB/Simulink. A major sector contributing to air pollution is the transport sector. Electric vehicles offer numerous advantages with respect to decreasing the overall pollution levels. The aim of this project is to understand the basic working of an electric vehicle by modelling and simulating it in the Simulink software. Basic Simscape Electrical as well as Simscape Driveline blocks are used to model the vehicle body as well as the driver inputs. A permanent magnet DC motor coupled to an H-bridge is used for four-quadrant voltage and current control. A lithium-ion battery is used to supply the voltage to the DC motor. The SOC of the battery is also measured during the simulation.**

***Index Terms*— first term, second term, third term, fourth term, fifth term and sixth term..**

I. Introduction

A Pure Electric Vehicle or also referred to as a Battery Electric Vehicle (BEV), is a vehicle operated entirely by an electric motor using stored onboard high-capacity battery packs. Generally called Electric Vehicles (EVs), Electric Vehicles utilize stored electricity to propel the motor as well as onboard electronics. The designs of Electric Vehicles are different than ordinary conventional internal combustion engine vehicles and they do not emit any type of harmful pollution or emissions. They are charged up by external means through Electric Vehicle (EV) chargers. For over a century, internal combustion engines have dominated the automotive industry, leading to extensive fossil fuel consumption and accelerated depletion of these non-renewable resources. The concept of using electric motors for vehicle propulsion dates back to the early 19th century. In light of growing environmental concerns and the need for sustainable alternatives, electric vehicles are gaining prominence as a cleaner, more efficient mode of transport. Advances in technology, especially for semiconductor devices, have improved the efficiency and dependability of motor control, additionally improving EV performance. Electric motive power development was initiated in 1827 with Hungarian priest Ányos Jedlik constructing an operational electric motor with a stator, rotor, and commutator that he subsequently applied to propel a small model vehicle. In 1835, Dutch professor Sibrandus Stratingh developed a scale model electric car, and Scottish inventor Robert Anderson developed a simple electric carriage from 1832 to 1839. That year, American blacksmith Thomas Davenport also constructed a toy electric locomotive using an early electric motor. In 1838, Robert Davidson, a Scotsman, developed an electric locomotive with a speed of up to 6 km/h.

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During the early times, the lack of availability of electricity grids and the limitations of battery technology kept electric cars from becoming widely accepted. But electric trains soon became popular owing to their efficiency and capability to attain useful running speeds. Electric cars were some of the first cars and played a leading role prior to the advent of low-weight, high-power internal combustion engines (ICEs).

II. Literature Review

The conventional methods of battery SOC are the impedance and internal resistance method, the open circuit voltage method, coulomb counting or ampere-hour counting method, and the electrochemical method [1]. Thevenin model was designed as the battery model appeared more suitable before studying the lithium-ion battery SOC estimation algorithm [2]. Robustness, accuracy and computation burden terms are compared and discussed in the SOC estimation methods [3]. The OCV (open circuit voltage)-SOC (state of charge) curve is most commonly used in SOC estimation and other battery management system (BMS) applications. Without preliminary experiments of battery model with simulated terminal voltages and to improve the accuracy of estimated SOCs, a new OCV-SOC curve estimation method is proposed [4]. Further the parameters of the lithium battery second-order RC equivalent circuit model are established and obtained. The EKF algorithm principle was introduced and applied as a secondary step in lithium battery SOC estimation [5].The SOC estimation based on traditional method on extended Kalman filter (EKF) is excessively dependent on the accurate battery model, and requires that the system noise must be subject to Gaussian white noise, and the SOC prediction error is large. Recurrent Neural Networks (RNN) is used to address the problems of SOC prediction error and to realize the accurate estimation of SOC [6]. Sigma Point Kalman Filter (SPKF) using joint battery model and SOC estimation method to achieve accurate estimation of the SOC when the battery is aged to adjust the battery model [7].

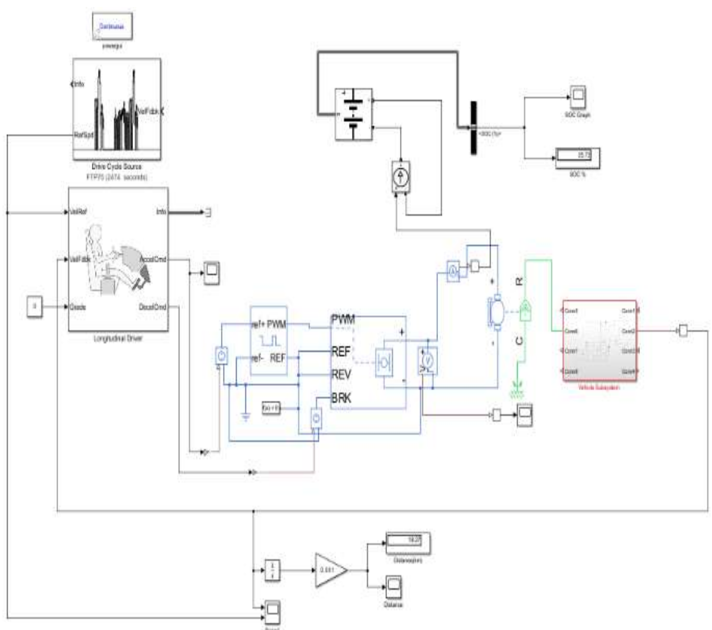

Figure I: Block Diagram of Proposed Model

The paper proposes a fuzzy prediction algorithm, and combines the simulation model of traditional econometrics for comparative analysis and obtains the final verification result, which improves the accuracy of SOC estimation, as it is difficult to accurately measure the state of charge of the battery because of the influential factors such as external temperature, charge and discharge current, the rate of change of battery internal resistance and battery lifetime [8]. A hybrid CC-LSTM algorithm was developed for SOC estimation and designs a dual-mode hardware architecture based on this algorithm. In addition, a test platform based on a field-programmable gate array (FPGA) is built to validate the proposed hardware [9]. The battery with a dual Bayesian estimation model scheme is used to obtain OCV-R-RC equivalent circuit. The parameter identification and SOC estimation both are treated in a Bayesian framework [10].

TABLE I: LITERATURE REVIEW TABLE

Author(s) & Year	Variables Studied/ Research	Design Model	Important Findings
Meng et al., 2019	Simplified model-based SOC estimation using dynamic linear model and Kalman filter	$LiFePO_4$ battery; PLS regression; linear Kalman filter; Simulink model for comparison	Proposed piecewise linear model avoids complex nonlinear filters and improves accuracy with reduced computational cost
Manthopoulos & Wang, 2020	Comparison of SOC estimation methods: Coulomb Counting, OCV, EKF, AEKF, Luenberger Observer, Neural Networks	Thevenin battery model with hysteresis; Simulink simulations on common dataset	AEKF was most robust against false initialization; Neural networks were most accurate but memory-intensive
Uthathip et al., 2021	Impact of SOC estimation on EV charging demand using stochastic modelling	Monte Carlo simulation; ANFIS for energy modelling; Transport survey data	SOC depends on both daily travel and driving behaviour; MCS-based method gives more realistic demand profiles for grid planning
Bin et al., 2021	SOC estimation using FFRLS and SFEKF; Hybrid battery-supercapacitor control	Thevenin battery model; FFRLS for parameter ID; Simulink/ADVISOR co-simulation	SFEKF+FFRLS reduced estimation error to ~3%; Coordinated control improved energy efficiency and battery life

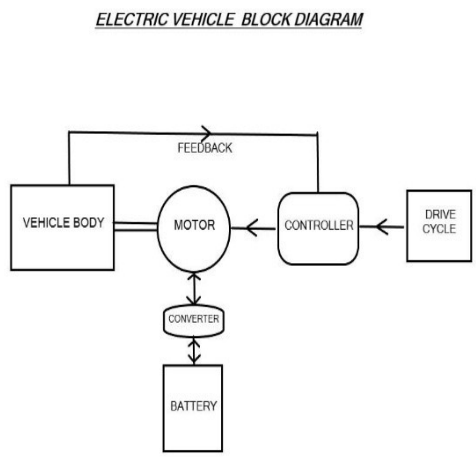

Figure 2: Block diagram of Electric Vehicle

III. METHODOLOGY

A. System Level Configurations

The various components of electric vehicle are categorized as below

- Vehicle Block Subsystem
- Motor and power converter
- Battery pack
- Drive cycle components

Vehicle Block Subsystem

The vehicle body represents the physical structure of the EV. The motor is mechanically connected to vehicle body through a transmission system and the wheels. The electric motor draws power from the battery based on the load demand, managed by a controller. The controller interprets load conditions and generates proportional control signals using feedback from the vehicle's sensors, ensuring smooth and efficient motor performance.

- Vehicle body: A two-axle vehicle body in motion is represented in this model. It accounts for key dynamic parameters such as the vehicle's body mass, road grade, aerodynamic drag, the centre of gravity and externally applied mass. The velocity of wind in m/s is represented as W and grade angle in radians is beta which are identified as input ports. NR represents normal force on Rear Axle (N), NF: normal force on Front Axle (N) and V: velocity in m/s. The output ports are NR.

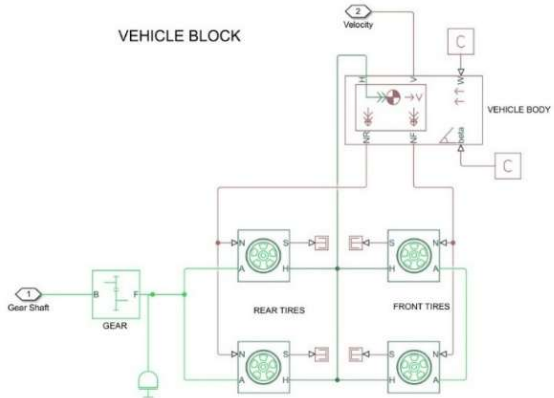

Figure 3. Vehicle Block Subsystem

- Tires: This block models the longitudinal behaviour of a tire using an empirical equation defined by four fitting coefficients. The capability of this model is simulating tire dynamics under both constant and variable contact surface conditions. Feature of analysing traction and slip characteristics in a range of driving scenarios is obtained. The input port is — N: Force is positive which is Normal when acting on tire is downwards/towards the contact surface. S is the output port which measures relative value of Slip with respect to tire and surface of contact. The two conserving ports are H: generated wheel thrust is transmitted to the body of the vehicle represented as wheel hub and A: mounting of tires on axle.
- Gear: The model uses a simple gear block for the connection between the motor and the vehicle's rear axle, effectively representing the gearbox. It transmits rotational motion from the input shaft (connected to the motor) to the base gear, and then to the output shaft via the follower gear, enabling torque and speed conversion as required by the drivetrain. The port B referred to as conserving port associated with motor shaft, referred as input shaft and port F is associated with axle/differential as output shaft.

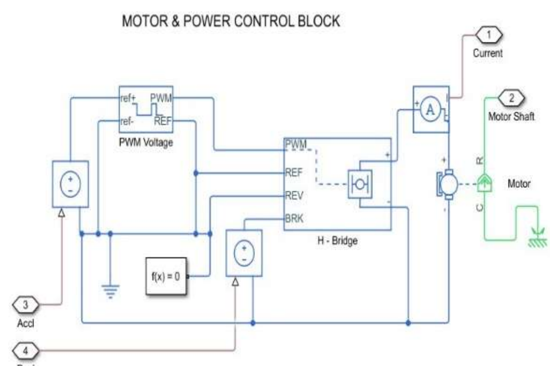

Figure 4. Motor and power converter

Motor and power converter

- DC Motor & H Bridge: A PMDC (Permanent Magnet DC) motor is used to convert electrical energy from the battery into mechanical motion to drive the wheels. It offers simple control, high torque at low speeds, and compact design, making it suitable for light EVs and low-power applications. An H-Bridge is used in an EV to control the direction and speed of a DC motor. It allows the motor to run forward, reverse, and stop by switching the polarity of the voltage applied to the motor, enabling efficient bidirectional control. It has positive and negative connection terminals, conserving ports associated with PWM control signal (PWM), zero voltage reference (PWM), bridge output signal voltage polarity (REV), and a signal when brakes are applied, for regenerative braking (BRK).
- Controlled PWM voltage: This block is responsible for producing pulse-width modulated signals to control voltage which are fed to H-Bridge as per requirements. It has positive and negative reference voltage signal ports, a zero-reference port and a PWM signal port.

Battery pack
The battery pack serves as the primary energy source of the electric vehicle (EV), supplying power to the motor and other essential components required for efficient vehicle operation. A power converter regulates and converts the electrical energy from the battery to match the voltage and current requirements of the motor. This converter is typically bidirectional, enabling it to channel regenerative braking energy back into the battery during vehicle deceleration, thereby allowing partial recharging. A bus selector is used to measure the battery's state-of-charge.

Drive cycle components
- Longitudinal driver block: This block functions as a longitudinal speed controller which generates acceleration and deceleration commands based on input and feedback speed variables with a Proportional-Integral (PI) control mechanism.

TABLE II: LONGITUDINAL DRIVER

Input ports	VelRef	reference input velocity in m/s
	VelFdbk	smooth control of the system is associated with velocity feedback from the vehicle
	Grade	inclination of surface in degrees with which it is associated
Output port	Info	a bus signal for acceleration, deceleration, error in velocity etc.,
	InfoAccelCmd	acceleration commands with reference to input signal,
	DecelCmd:	deceleration commands with reference to the input drive signal.

A drive cycle source is used in simulation to represent a standardized driving pattern, providing reference input based on real-world or test cycle data to evaluate the vehicle's dynamic behaviour under typical driving conditions. We have used the FTP75 drive cycle for this project.

IV. RESULTS

Simulation is conducted to evaluate the performance of the model built by monitoring the speed comparison between the feedback and reference signals and the state-of-charge of the battery. The FTP-75 drive cycle was employed in the simulation, taking 1875 seconds. The speed comparison plot indicates that the actual speed of the vehicle (blue line) closely follows the reference speed (yellow line) during the simulation. Small variations occur during the sharp deceleration phases due primarily to the inertia of the vehicle and sudden decreases in speed encountered by the reference profile. As per distance, the vehicle covers approximately 17 kilometres in 1874 seconds with the help of the FTP-75 drive cycle. The FTP-75 drive cycle is for 11.04 miles (17.77 km) total distance and is 1874 seconds long, with an average speed of 21.2 mph (34.1 km/h). In simulation, the Display block is used to display the distance the vehicle has travelled in kilometres. The vehicle has travelled approximately 13.6 km at the end of the simulation, at 1874 seconds. The observed variation represents the variation in the instantaneous velocity within the drive cycle data, which is not precisely replicated by the real-world driving conditions of the vehicle. Better parameterization will make the drive system more uniform, and the vehicle will mimic the drive cycle more accurately. This will reduce velocity deviations and ultimately cause the vehicle to cover a longer distance.
State-of-Charge (SOC) of battery: The FTP75 drive cycle has a number of acceleration and deceleration profiles, which vary randomly and reflect actual driving patterns. With this variation, it mimics the pattern of the battery discharge under various acceleration conditions, in addition to the effect of regenerative braking during deceleration. The State-of-Charge (SoC) block monitors the remaining capacity of the battery. The SoC of the battery varies from 100% to around 70% after covering a distance of 13.6 km in about 30 minutes.

V. CONCLUSION

An electric vehicle with basic functionality model was developed using SIMULINK, and the simulations were performed according to the FTP75 drive cycle and Wide-Open-Throttle (WOT) conditions. The time of simulation for the FTP75 cycle was reduced to 1874 seconds, while for the WOT condition, it was kept at 60 seconds. The velocity comparison curve exhibits a good performance from the model, which attempts to meet desired levels of acceleration and deceleration commands. This is apparent from the very small differences between the actual drive cycle curve and the velocity feedback curve. Depth of discharge under the FTP75 drive cycle, as per the simulation, is roughly 30%, wherein the vehicle can cover a distance of 13 km in around 30 minutes.

A more precise and comprehensive parameterization of the vehicle block and motor control variables will allow the model to follow more closely the reference velocity signal and thereby improve the system's performance. Another battery block variable adjustment has the capability of reducing the Depth of Discharge, leading to greater mileage on every charge-discharge cycle. Additionally, tuning the block variables to minimize the discrepancy between the reference and output speed signals, as well as battery pack optimization for better mileage and peak performance, would enhance overall performance. Running extensive simulations, rather than employing averaged mode simulations, would provide a more realistic and efficient model.

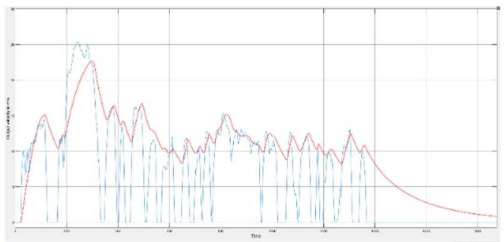

Figure 5. Speed graph

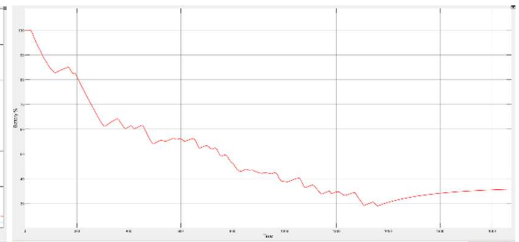

Figure 6. SOC graph

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