Simulation Model for Rendering and Analyzing the Prediction of Electric Vehicle Energy Consumption in Matlab/Simulink

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Abstract: This work presents the development of a simulation model for predicting the electricity consumption of electric vehicles (EV), with a focus on creating a model that enables precise monitoring of the electric vehicle battery's state. A simple method is provided for predicting the state of charge (SoC) of electric vehicle batteries without computational complexity and other processes. The relevance of the study is demonstrated through the ease of adaptability to all types of electric vehicles, using reliable methodologies for predicting the energy consumption of electric vehicles. This approach aims to contribute to the advancement of the technological infrastructure of electric vehicles, chargers, and routing application software.

1. INTRODUCTION

Predicting energy consumption for EVs represents an unpredictable task that depends on a range of variables including, vehicle characteristics, driver's driving habits, road topography, weather conditions, traffic conditions, and other elements. To maximize battery efficiency, plan travel routes, and improve overall vehicle performance, a simulation model for EVs developed using Matlab/Simulink enables greater accuracy in estimating the energy consumption of EVs on a given route.

The motive of this research is to improve the model for predicting EV electricity consumption, which overcomes the limitations of existing methods and reduces the range anxiety of EV drivers. The goal is to develop a simple simulation model that allows more accurate prediction of EV battery consumption in real driving conditions, especially through simulation on global routing platforms.

By creating an offline/online technique using open-source route information and a simplified longitudinal vehicle dynamics model, the authors in [1] demonstrated the accuracy of the proposed technique at 5% for the online method and 10% for the offline

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method through driver tests conducted on public roads. In comparison with FASTSim , a high-level powertrain model created by NREL [2], the authors in [3] provided a computationally efficient energy consumption model.

Energy usage models are also of interest in eco-driving and eco-routing applications, with different models used in [4][5][6][7]. Researchers in [8] categorized energy consumption prediction techniques into two categories based on vehicle longitudinal dynamics and statistical methods that rely on energy measurement by EVs and real-world data. Some studies focus on consumption estimation using neural networks to characterize the environment in which the EV operates and estimate energy consumption using average conditions [9].

Research conducted in the United States in collaboration with the United Nations Framework Convention on Climate Change (UNFCCC) indicates that the transportation sector is responsible for the largest share of greenhouse gas emissions, accounting for approximately 29% worldwide [13]. According to research conducted in Europe, the transport sector generates around a quarter (23%) of the current global greenhouse gas emissions related to energy and is a leading cause of air pollution [14].

The International Energy Agency (IEA) predicts that without significant intervention, greenhouse gas emissions from transportation will increase by nearly 50% by 2050 [14]. To achieve this transition, between 20% to 30% of all road transport vehicles must be electrified globally by 2030 through the Paris Climate Agreement and the EV30@30 campaign [10]. These agreements unite signatory members in the fight against global climate change and establish a common aspirational goal of road traffic electrification.

Through the introductory chapter, the basic concept is presented, while the second chapter deeply analyzes the Matlab block diagram for EV simulation within the Simulink software program, enabling a detailed understanding of EV functionality. The model configuration is realized through EV modeling in Matlab, which facilitates the analysis of the vehicle's behavior in different driving scenarios, focusing in particular on the effects of the forces acting on it. The graphs showing the EV simulation results throughout the third chapter vary depending on the type of test and the selected parameters. The quality of the obtained results depends on the quality of the underlying data. The final chapter provides a retrospective of the entire work and identifies future trends, while at the end there is a list of literature that was used in the research.

This paper presents a physical model of an EV developed in the Matlab/Simulink graphical programming environment. The physical model allows for the identification of vehicle and road parameters that affect consumption. The developed model is created based on the mechanical and electrical characteristics of EVs that can be personalized to fit different EV models. Using available data from the Tesla Model S EV model, graphical and numerical results of energy consumption are presented through an open driving cycle obtained for a real route using the OpenStreetMap (OSM) platform.

2. METHODOLOGY OF SIMULATION MODEL DEVELOPMENT

To perform a simulation of EV energy consumption prediction in Matlab, we first need to have a fundamental understanding of the block diagram that describes how the EV functions. The basic block diagram of the EV operation is presented in Fig. 1.

The simulation of the physical model of an EV is one of the many simulations that can be done in Matlab and is significant for the purposes of this work. To initiate the simulation, the first step is to incorporate a block that represents the vehicle body and tires. This block will then specify the differential in the gears, as well as all other relevant data related to the vehicle assembly. Next, the controller and motor need to be positioned in the block diagram, which takes input from the driver about driving cycles, i.e., the amount of throttle input from the driver.

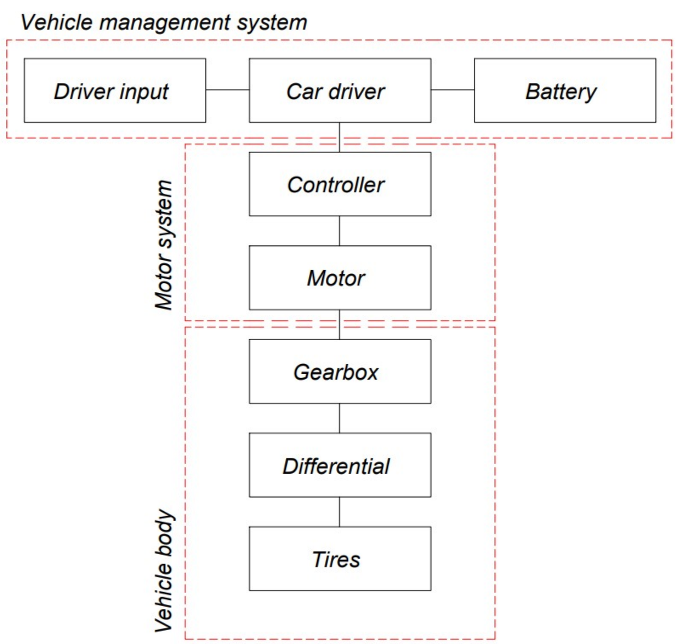

Fig. 1. Basic block diagram of EV functioning in three units

The Simulink model for predicting EV energy consumption is presented in Fig. 2. The main input to the Simulink model is the Driving cycle block, which describes the progression of the vehicle's speed over time. The speed tracking controller included in the Longitudinal driver block uses the driving cycle as a reference signal to track the vehicle's speed. The speed tracking controller is a proportional-integral (PI) controller that generates normalized acceleration and braking commands based on the difference between the reference speed and the measured speed. The PI controller also allows for the provision of the elevation profile along the observed path. In this way, acceleration and braking control are represented depending on the road's topography, enabling the use of such a controller on real-world routes.

In the separate Motor drive diagram, illustrated in Fig. 3, the normalized acceleration and braking commands issued by the Longitudinal driver block are reflected as inputs to the DC

Motor block. This work focuses on EVs that are powered by DC motors for simplicity. The H-Bridge serves as the controller for the DC motor. The normalized acceleration command is modified to be transformed into an acceptable voltage value at the input of the H-Bridge using a PWM-controlled voltage source.

A short circuit is created at the output of the H-Bridge as a direct result of the braking command, which, in turn, leads to the interruption of the power supply to the DC motor. A flyback diode is included in the H-Bridge to prevent voltage spikes in case of abrupt power interruption. By simulating the operation of the DC motor in response to acceleration and braking commands, it is possible to determine the change in the torque on the motor's crankshaft and the change in the current the motor produces over time. These two values are the primary outputs generated by the Motor Drive block.

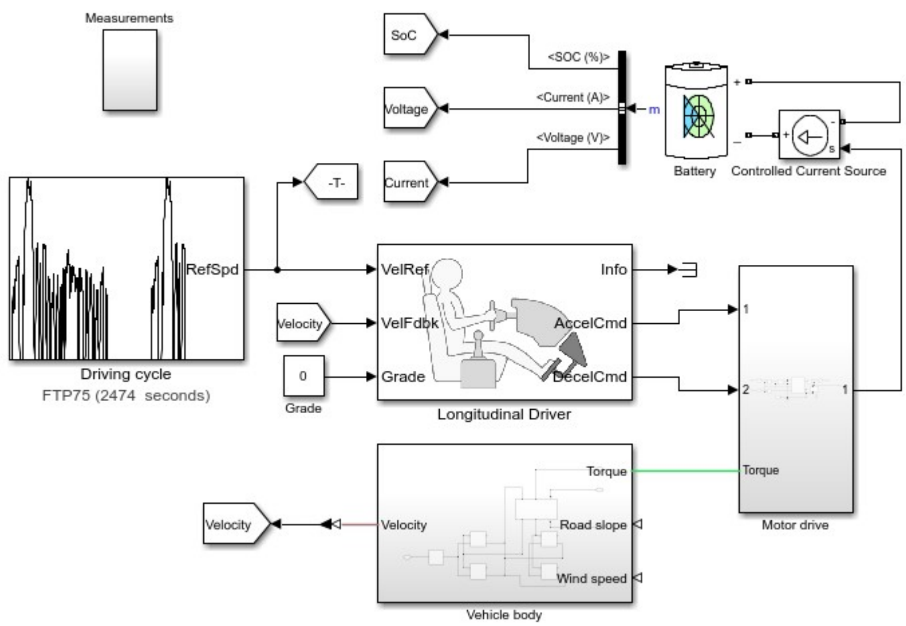

Fig. 2. Matlab/Simulink model for predicting electric vehicle energy consumption

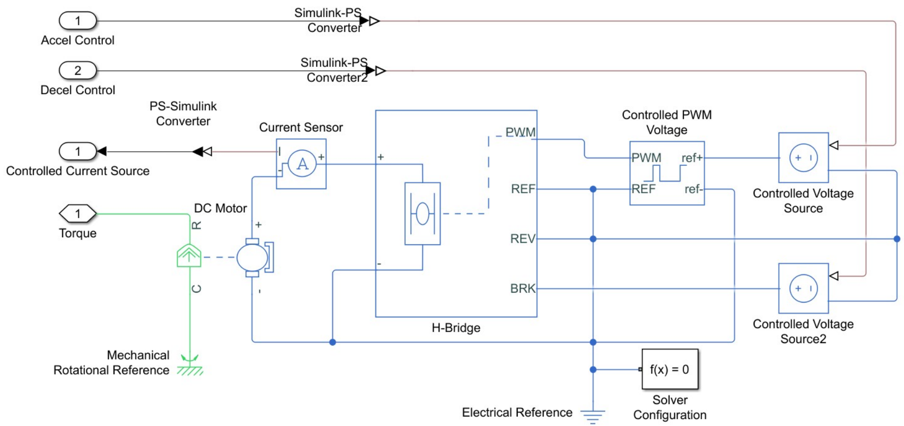

Fig. 3. Simplified diagram Motor drive

The main input of the Vehicle block can be seen in Fig. 4, represented by the torque applied to the motor shaft. The vehicle's wheels are not directly connected to the motor shaft; instead, a transmission system is used to link the motor shaft to the wheels. The transmission system is designed to adjust the speed and torque at the motor shaft to appropriate levels at the wheels. The transmission ratio, as well as its efficiency, describes the transmission system, and for the Tesla Model S electric vehicle, it is 9.734:1. This transmission ratio varies depending on the type of vehicle.

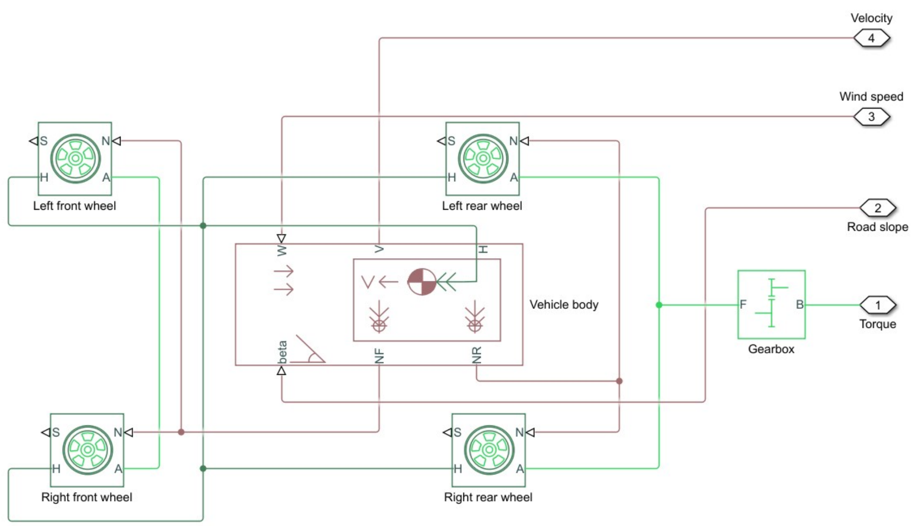

Fig. 4. Simplified diagram Vehicle body

The vehicle motion model variables are defined in Fig. 5. By using the interaction that occurs between the wheels and the asphalt surface of the road, the formula is modeled to calculate the traction force Ft acting on the wheels. When the values in (1) are known, it is possible to calculate the new vehicle speed resulting from the acceleration and braking outcomes. The signal from the deviation of the speed-tracking PI controller located in the Longitudinal driver block is formed using the measured vehicle speed in a negative feedback loop, allowing the signal to be as accurate as possible [11].

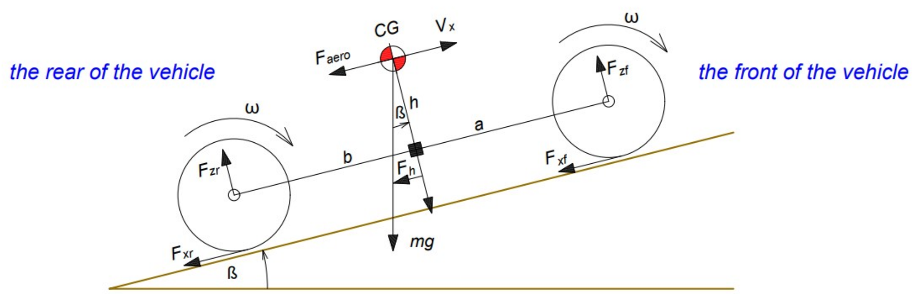

Fig. 5. Vehicle body block illustrating the forces and motion of the body of a two-axle vehicle

Based on the previously mentioned effects of forces from Fig. 5, the total traction force of the vehicle would be the cumulative sum of all forces acting on the moving vehicle.

$$\mathrm{F_t} = \mathrm{F_{xrr}} + \mathrm{F_{aero}} + \mathrm{F_h} + \mathrm{F_a} + \mathrm{F_{\omega a}} \tag{1}$$

Where F_{xrr} represents the rolling resistance force:

$$\mathrm{F_{xrr}} = n \cdot \left(\mathrm{m} \cdot \mathrm{g} \cdot \mu_{\mathrm{rr(front)}} + \mathrm{mg}\mu_{\mathrm{rr(rear)}}\right) \tag{2}$$

Here ‘n’ is the number of wheels on the vehicle, ‘μ_{rr}‘is the rolling resistance coefficient for front and rear wheels, ‘m’ is the total mass of the vehicle including passengers, ‘g’ is the acceleration due to gravity.

The equation for the aerodynamic drag force can be presented as:

$$\mathrm{F_{aero}} = \frac{1}{2}\rho \cdot \mathrm{A} \cdot \mathrm{C_d} \cdot \nu^2 \tag{3}$$

Where ‘A’ is the frontal area, ‘v’ is the vehicle's speed (this equation is extended in some publications to include the influence of wind on the vehicle's motion), ‘ρ’ is the air density, and ‘C_d’ is the drag coefficient. Factors such as temperature, altitude, and humidity affect air density.

The simplest vehicle motion would be on a horizontal surface with no inclination, but that is not the case in practice, which is why it is necessary to find the force that allows the vehicle to move on some terrain slope. The simple resolution of the force F_h allows us to consider the vehicle's motion on an inclined angle β, with (4).

$$F_h = m \cdot g \cdot \sin\beta \tag{4}$$

In addition to the forces shown in Fig. 5, another force will undoubtedly be required when the vehicle's speed changes. The acceleration force Fa largely depends on the transmission system that defines further acceleration or deceleration of the vehicle:

$$F_a = m \cdot a \tag{5}$$

Rotating circular bodies also require angular velocity, and knowing that angular velocity ω is equal to the ratio of speed to the tire radius, the creation of angular acceleration force $F_{\omega a}$, represented by the equation for the axle speed with the gear ratio, would be:

$$F_{\omega a} = I \cdot \frac{G^2}{r^2} \cdot a \tag{6}$$

Where 'I' represents the moment of inertia of the motor rotor, 'r' is the tire radius, and 'G' is the gear ratio of the system connecting the motor to the axle.

The change in motor current over time is used to determine the change SoC of the battery using the Battery block, which implements a generic model of lithium-ion batteries commonly used in the industry. With the discharge or charge current, the change in SoC over the time period 'dt' can be represented through (7) and (8) as follows:

$$\Delta SoC = \frac{idt}{Q(i)}[\%] \tag{7}$$

where 'Q(*i*)' is the battery capacity expressed in Ah, and '*i*' is the discharge or charge current. During the battery discharge process, the current is positive, while in the case of charging the battery, it is negative. According to this definition, a fully charged battery has a SoC of 100%, while an empty battery has a SoC of 0%.

$$SoC = SoC - \frac{1}{Cn}\int_0^t I(t)dt \tag{8}$$

In the next chapter, the rendered results of vehicle energy consumption simulations on a test drive cycle will be presented, analyzing the impact of road inclination using the OSM platform.

3. PREDICTION RESULT RENDERING

The electric vehicle model, Tesla Model S, with a maximum motor power set at 280 kW and a maximum torque of 420 Nm, has been adapted to the Matlab/Simulink EV model. It is powered by a 100 kWh lithium-ion battery, with an expected typical range of 360 km [15]. The transmission system with a fixed gear ratio of 9.734:1 connects the wheels and the motor. The vehicle's weight without passengers is 2,200 kg.

The proposed approach needs to be evaluated, considering real route conditions, using some of the routing libraries currently available on the Internet worldwide. The simulation model of the EV will be tested using a real route obtained through OSM, an open project that provides route information such as road types and speed limits based on origin and destination. GraphHopper is an open-source Routing Framework that can be used to determine the optimal route between two locations on the map. It allows users to incorporate routing functionality into their applications and customize routes to their specific requirements. GraphHopper uses graphs and pathfinding algorithms to determine the fastest or shortest path between two points. It can utilize various data sources, such as OSM and Google Maps, and offers the option to use different pathfinding algorithms, including Dijkstra's algorithm [12]. GraphHopper is renowned for its usability and adaptability.

Using GraphHopper, data for a route starting in Podgorica (42.4304, 19.2594) and ending in Split (43.5147, 16.4435) were collected. Fig. 6 shows the route and the elevation profile along the path. GraphHopper returns a segmented path together with the attributes of each individual segment. Because the driving cycle returned by GraphHopper is a discontinuous set of data, it needs to be preprocessed before it can serve as input to the model. This data processing task is achieved using the Matlab programming language, which provides accurate and reliable results that meet the end-user's requirements. The entire driving cycle is computed according to the speed limits in effect along the requested route. Hence, point interpolation is embedded in the driving cycle to simulate traffic and speed deviation from the speed limits, enabling more precise simulations.

Fig. 6. Display relevant GraphHopper map information, including geographic location, distance, altitude, and route duration between two locations

The data retrieved from GraphHopper requests were processed using Matlab code and are illustrated in Fig. 7, showing the analyzed information on the driving route, elevation difference or terrain slope, and maximum speed limit during different time segments of the journey. The predicted route has a typical travel duration of just under 5 hours, with a total distance of about 340 km. The estimated consumption of a fully charged battery SoC for the developed simulation EV using the Matlab/Simulink approach for predicting energy consumption based on OSM platform data corresponds to approximately 92.4% of the battery for the entire trip. The amount of energy consumed is proportional to the expected typical performance range provided by the Tesla Model S vehicle, giving extremely high reliability and relevance in the calculations with a deviation of 1.83% compared to the ideal conditions achieved by the Tesla Model S in real-world conditions. The proposed Matlab/Simulink model for consumption predictions represents a useful tool for rendering the amount of energy consumed before the EV completes a specific desired distance.

For rendering the results, both numerical and graphical designs can be used. The results will be graphically rendered, as shown in Fig. 8, displaying the traveled distance, battery consumption, vehicle speed, and the dependence on current and voltage changes from previous visual displays.

The rendered results shown in Fig. 8 were obtained under the assumption that the influence of wind is neglected, which is a risky assumption for real routes. The developed simulation model of the EV allows for changes in wind speed, preventing underestimation of energy consumption based on specific route data.

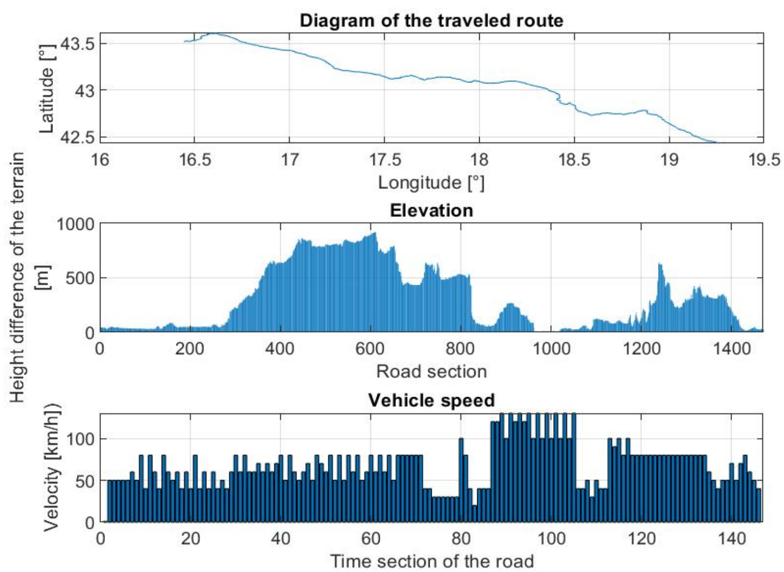

Fig. 7. Graphical comparison of Graphopper platform data through Matlab simulation using API route between two locations

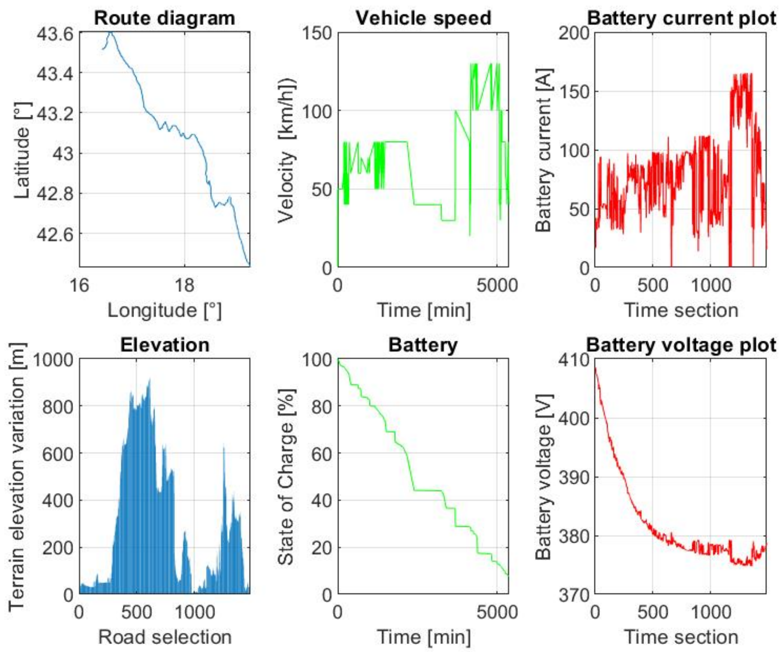

Fig. 8. Graphic display of energy consumption in a certain area (Podgorica-Split)

4. CONCLUDING CONSIDERATIONS

This study has successfully achieved its main goal, which is to provide the end-user with a constructed model that yielded highly accurate results for predicting the energy consumption of EV batteries using real-world data, thus guiding EV users in their pursuit of energy efficiency. Based on the obtained results rendered in the previous section, it can be concluded that this developed model represents a simple and efficient solution for predicting the energy consumption of EVs. The proposed MATLAB/Simulink model further enables the incorporation of road characteristics and weather conditions' impact on energy consumption. MATLAB and Simulink are efficient tools for modeling, simulating, and analyzing dynamic systems, making them essential instruments for testing electric vehicle battery consumption. It has been demonstrated that these tools allow for precise measurement of SoC and prediction of EV consumption based on simulation.

The developed model is a physical model that includes both mechanical and electrical components of the vehicle. The driving cycle is used as a reference signal for speed control, generating acceleration and braking commands, thereby controlling the vehicle's motor. The model parameters are personalized according to the available data for the Tesla Model

S. The model's performance is evaluated on an open road driving cycle obtained for a real route using the OSM platform.

The developed model is stable and reliable, considering various testing possibilities. However, the proposed model relies on certain assumptions, such as neglecting auxiliary power consumption in the vehicle, although it can easily be included by superimposing the auxiliary load current on the motor current and neglecting regenerative braking efficiency. Despite the mentioned limitations, the proposed model provides a computationally efficient and reliable solution for a rough estimate of energy consumption on a predefined driving cycle.

The implementation of these methods enables precise analysis of vehicle performance in a real environment, providing valuable support for optimizing EV performance. The predictions of the model presented in this study are limited to the prospects of future integration with the Open Charge Point Protocol (OCPP) protocol. This study offers the possibility of predicting the energy consumption of EVs to improve the technological infrastructure of EVs, their chargers, and application software, enabling users to forecast the energy consumption of their EVs.

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