ENERGY CONSUMPTION MODELING AND OPTIMIZATION OF SPEED PROFILE FOR PLUG-IN ELECTRIC VEHICLES

A Thesis

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ENERGY CONSUMPTION MODELING AND OPTIMIZATION OF SPEED PROFILE FOR PLUG-IN ELECTRIC VEHICLES

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ABSTRACT

In recent years, there is a surge in research on Plug-in Electric Vehicles (PEVs), as PEVs are one of the ways that we can reduce carbon emissions. Dramatic cost reduction in PEVs has resulted in their becoming mainstream vehicles. However, there is still one big hurdle before they can take over other types of vehicles, and that is their limited range. Lack of charging stations exacerbates the situation further, and proliferation of charging stations does not completely alleviate the range problem as charging can take a few hours. Therefore, a PEV should cover as much distance with a given battery charge, or equivalently, should consume as little energy as possible for a given distance. The choice of the instantaneous control algorithm plays a role in this energy minimization problem, but on the other hand, the most critical aspect of this minimization problem is the speed profile of the vehicle, which is given as a reference input to the instantaneous control algorithm. This thesis offers a significant contribution to the literature in range optimization of PEVs given a realistic vehicle model, which it does through a combination of Monte Carlo and Newton-Raphson optimization methods.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

In today's world, energy is an important resource for humankind. Many climate scientists show that the main reason for current global warming is due to the greenhouse effect created by humankind. In other words, atmospheric carbon dioxide (CO2) is increased due to the burning of fossil fuels such as coal and oil over the last century. Furthermore, some other effects are reported according to [1]. So, reducing carbon emissions and improving air quality must be a high priority by today's humankind for future generations. Furthermore, the rapid rise of demand to vehicles around the world and so the demand for fuel will increase more carbon emissions unless electric vehicles replace conventional vehicles with internal combustion engines.

There are different types of electric vehicle technologies depending on the type of energy source. Battery electric vehicle (EV), Plug-in hybrid electric vehicles (PHEV), Hybrid electric vehicles (HEVs) and Fuel-cell electric vehicles (FEV) describe different technologies of an electric vehicle. Battery electric vehicles run completely on their electric battery. They do not have any alternative source of energy to switch if the charge of the battery is depleted. There are standard charge stations with which this type of vehicles is charged, however, in order to have longer range, they are required to be charged completely. Plug-in-Hybrid vehicles are vehicles with a combination of an electric motor with a conventional internal combustion engine. However, plugging the vehicle into a special charge station is required in order to charge the vehicle. These vehicles can switch to traditional fuel power when the electric motor is unable to provide the required power. Hybrid electric vehicles are known as vehicles with a normal internal combustion engine and an electric battery. It is not required to charge its battery externally, but it is charged by the vehicle itself while the car is running using the energy provided by the conventional engine. FEVs are cars with an electric motor which is charged through a combination of hydrogen and oxygen in order to create a chemical reaction [2].

1.1 Motivation

Limited driving range and long charging time of battery electric vehicles (BEVs) are the most challenging issues for the driver concerned about arriving to a destination which is called "range anxiety" [21].

Furthermore, driving patterns (i.e. driving conditions and driving range) are an important issue in energy consumption, economic costs, and environmental impacts. Driving conditions such as driving speed, acceleration, idling time, etc. directly determine the energy consumption of the vehicles [3-6].

Obviously, the driving range can be extended by using a large battery, but the battery gets heavier and costs more. Also, building fast charging stations needs more investments and it cannot be as widespread as fuel stations.

1.2 Previous studies

Many researchers are studying to overcome technical obstacles such as battery technology limitations [22-25], charging infrastructure problems [26-29] and improving electric motor and powertrain performance [30, 31]. One approach to extend the driving range is improving the performance of regenerative braking [32]. In order to extend the driving range, most of the researchers work on regenerative braking by developing a control strategy like fuzzy logic control [33,34] or model predictive control (MPC) [35] which has attracted more attention. Prins *et al.* [36] used a simple vehicle efficiency based on the prediction of the motor manufacturer for modeling of energy estimation, disregarding the regenerative braking system. Shankar and Marco [37] predicted energy consumption over a route under real-world driving conditions, considering traffic type and congestion. The accuracy of the prediction of the proposed approach varied between 20-30 and 70-80 percent. K. Sarrafan [38] proposes an improved method for the state of charge (SoC) and range estimation by consideration of location-dependent environmental conditions and time-varying drive system losses. Several energy management approaches for an electric vehicle has been presented and discussed by previous researchers. To manage the utilization of battery energy intelligently through a combination of GPS and road topographical data, a control software has been developed in [7]. An efficient energy-management has been proposed in [8], which extracts velocity trajectory using intelligent transportation system technologies for PHEV. Y. Chen proposes an EMDS design to minimize the energy consumption of a trip, which extends the traveling distance based on information of the road terrain profile and the preceding vehicle [9]. An energy management system based on an equivalent consumption minimization strategy (ECMS) has been discussed in [10]. L. Xu develops a real-time optimal energy management strategy based on the determined dynamic programming (DDP) strategy [11]. C.Lin presents an approach to solve optimal power management using dynamic programming (DP) in the hybrid electric truck [14]. Q. Li suggested a fuzzy logic implemented in the ADVISOR software for FC/B and FC/B/SC vehicles to improve the fuel economy and increase the distance traveled. This method gives better fuel economy and driving cycle conditions but the battery or supercapacitor SoC information are not expressed in this paper [12]. H. Hemi utilizes a fuzzy logic controller to manage power between a fuel cell as a primary source and battery and supercapacitor as secondary sources in a hybrid vehicle [13]. Denis *et al.* proposed a fuzzy-based blended energy management strategy with focusing on driving conditions of the plug-in hybrid electric vehicle, and simulations demonstrated the efficiency of the proposed strategy [15]. Li *et al.* proposed an optimal fuzzy power control strategy for fuel battery hybrid vehicles and simulation results confirm its good performance in fuel economy and overall system efficiency [16]. C. Sun compares three types of velocity predictors for MPC-based energy management in a power-split HEV [17]. Erdinc O. introduces the wavelet fuzzy logic strategy to control and distribute the required power from the power sources to the load [18]. Kaijiang YU proposed a velocity control system based on MPC to save the fuel consumption using traffic signal information [19]. A. Mozaari and J. L. Sanz employed a model predictive controller strategy for the EMS of the battery-SC H-ESS. MPC has shown to be a suitable solution for a variety of applications in vehicle control [39-40]. Zhihong Yu *et al.* presented a new optimal strategy for minimization of vehicle energy consumption which makes the global optimization into a real time control [41]. P. Cocron, F. Millo, and C. A. Silva suggested a model which can describe the electric vehicle's traffic, but they cannot be used to investigate the effect of the road's slope on the electric vehicle's electricity consumption. S.C. Yang investigated the effect of the slope of the road on EVs energy consumptions under different traffic states [20]. E. Khmelnitsky presented optimal control based on the Maximum Principle which minimizes the energy consumption for driving the train from one point to another point subject to the variable grade profile and speed restrictions. However, the algorithm is purely open-loop and it can be applied in real-time feedback design [67]. C. Lin presented power management control algorithm for hybrid electric vehicles by using Markov chain modeling and stochastic dynamic programming techniques. The future uncertainty of the driver power request under diverse driving conditions is modeled after a Markov process. Finally, the author compares stochastic dynamic programming (SDP) control strategy with the sub-optimal rule-based control strategy [68]. H. Ko presented the optimal control problem for minimization energy consumption by a train based on Bellmans Dynamic Programming [69]. S. Stockar presented a new approach for the supervisory energy management of PHEVs. The author formulated an optimal control problem by defining a cost function based on the cumulative CO_2 produced by the vehicle.

Also, Pontryagins Minimum Principle is applied to reduce a global optimization problem to a local minimization. Finally, the control algorithm was implemented on an energy-based PHEV simulator and validated on experimental data. They collected a large database and investigated driving profile characteristics on different driving cycles [70]. S. Kermani presented real-time control strategy based on optimal control theory and applied to a parallel HEV on a predefined route and then implemented in a power-hardware-in-the-loop (PHIL) simulation. The Lagrange optimization approach applied the optimal engine and electric motor torques. Experimental results show improved energy consumption as well as a good battery SoC control based on proposed method. Also, the robustness of the method has been tested for different reference routes [71]. F. Mensing presents a dynamic programming optimization approach to optimize the efficiency of a vehicle. The proposed method is not suitable for real-time implementation. Also, using eco-driving strategies can improve fuel economy up to 16%. Also, NEDC (New European Drive Cycle) is used as a drive cycle in [72]. J. Wollaeger presented a solution for optimization problem based on cloud optimization which generates the optimal speed profile to minimize the conventional vehicles fuel consumption. The fuel optimization cost function was transformed from the time domain to spatial domain and is minimized using a spatial domain discrete dynamic programming. Also, optimal velocity profile in real-time is recalculated in response to external traffic disturbances through the proposed method and real-time road traffic information [73]. K. Boriboonsomsin presented an eco-routing navigation system which finds different optimal routes for the same trip in order to minimize the fuel consumption or emissions between a trip origin and a destination [74]. A. R. Albrecht presents perturbation analysis to solve the problem of Energymiser device which cannot find optimal switching points for each steep section of track uniquely. Thus, the global optimal strategy is unique [75]. W. Zeng investigates the fuel consumption prediction for a trip based on the support vector machine (SVM) method by considering some variables such as trip distance, average travel speed, intersection density, COV of link speed, and engine displacement. The author compares the performance of the SVM model, Least squares support vector machine (LSSVM) model, Logistic regression (LR) model and Artificial neural network (ANN) model. In summary, the proposed method guarantees the global optimum fit [76]. T. Jurik proposes an energy optimal real-time navigation system (EORTNS) which is implemented on a tablet computer in order to calculate the route to the destination based on the information flow obtained from SYTADIN (a Real time traffic information system) [77]. F. Jimnez preseneted an optimization system based on dynamic programming theory in order to minimize the fuel consumption in vehicles with a conventional power-train. The produced optimal speed profile is provided to the driver in real-time. Also, the proposed method guarantees reaching the destination on time by considering speed limits and possible traffic jams, as well as the information obtained through wireless communications [78]. P. G. Howlett proposes an approach to calculate the critical switching points for each steep section in a globally optimal control strategy separately by applying a new local energy minimization principle over each steep section [79]. L.Wang presented an optimization problem for minimization of fuel economy based on choosing three parameters: the total weight of the ESS (energy storage system), the UC weight ratio, the DH (degree of hybridization). The goal of the proposed method is not only to extend ESS cycle life, but also to decrease the total ESS loss as well, which leads to improving the equivalent fuel economy [80]. A. R. Albrecht proposed the two-train separation problem in order to minimize the total energy consumption and allow both trains to finish on time. An optimal solution with prescribed intermediate clearance times is presented to find energy efficient driving strategies for both [81]. M. Masikos proposed estimation of energy consumption using machine learning method. The author collected data with a driving vehicle to create training data. The robustness of the proposed method is verified by the contextual parameter changes (e.g. different traffic conditions) [82]. E. Ozatay solved the optimization of the speed trajectory by a spatial domain dynamic programming (DP) algorithm in order to minimize the fuel consumption. Also, road geometry and traffic conditions are taken into account for this goal. Test results show an improvement of around 5-14% in fuel economy depending on the driver and the route [83]. M. Miyatake presented a literature review in line with optimal control theory. The author introduced three methods including dynamic programming (DP), gradient method, and sequential quadratic programming (SQP) [84]. G. Heppeler introduced the algorithm for long-horizon battery planning and the optimal control problem for the combined SoC and velocity planning on a shorter horizon for HEV. The method is tested in simulations and compared with the results calculated by an offline discrete dynamic programming algorithm in order to determine the overall fuel savings potential [85]. N. Wan proposed a predictive cruise control approach which takes the position distribution prediction of the preceding vehicle as an input and minimizes a cost function with probabilistic intervehicle constraints in a receding horizon manner. Also, the author introduced two predictors and using combined predictor car-following costs is reduced according to simulation results [86]. O. Gomozov developed a real-time management strategy supported by a model predictive control (MPC) using the nonuniform sampling time concept. According to real-time simulation results, the proposed MPC strategy can balance the power and the energy of the dual energy storage system more effectively and reduce the stress on batteries [87]. S. Uebel presented a new approach for online optimal control of hybrid electric vehicles (HEV) based on a combination of discrete state-space dynamic programming and Pontryagins Maximum Principle. The proposed approach yields a close-to-optimal solution by solving the optimal control problem over five orders of magnitudes faster [88].

1.3 Outline of the thesis

This thesis discusses speed optimization of PEVs using detailed vehicle model and contains seven chapters. Chapter 2 introduces the dynamic model of electrics vehicle and then energy consumption model including the regenerative braking. In Chapter 3, Monte Carlo approach is presented to minimize the total energy consumption. In Chapter 4, Newton Raphson method is also presented to improve the optimization method. In Chapter 6, the efficiency of motor and inverter was studied in details. In Chapter 7, the Monte Carlo method is tested on different routes. Finally, conclusions and recommendations for future work are presented.

CHAPTER II

DEFINITION OF THE PROBLEM

The energy Consumption of the vehicle for various driving conditions requires to be identified for future powertrain efficiency improvements. So, kinematics and the dynamic vehicle is crucial requirement to investigate energy consumption of the vehicle.

2.1 Kinematics

Kinematics is a branch of classical mechanics, which describes the motion of a point, a body without considering the mass factor and forces that created the motion. The route is divided into small segments of size roughly equal to the length of a passenger vehicle. The acceleration of the vehicle is assumed to be constant in each segment. In this study, the kinematics formulas are a set of equations that relate five kinematic variables listed below:

Δt_i : time duration in each segment

Δr_i :length of segment

v_i : initial speed at the beginning of the segment

v_{i+1} : final speed at the end of the segment

a_i :acceleration in each segment (constant)

Constant acceleration yields, the following kinematics equations in each segment:

$$v_{i+1} = v_i + a_i \Delta t_i \tag{1}$$

$$\Delta r_i = v_i \Delta t_i + \frac{1}{2} a_i . \Delta t_i^2 \tag{2}$$

$$\Delta t_i = \frac{2\Delta r_i}{v_i + v_{i+1}} \tag{3}$$

$$a_i = \frac{v_{i+1}^2 - v_i^2}{2\Delta r_i} \tag{4}$$

Figure 1 shows the speed and acceleration for a specific route, as an example. The goal of this graph is to explain the behavior of speed-position and acceleration-position. The path is divided into N segment and each segment (Δr,Δh,f_{roll}, or any other geometrical value) does not have to be identical. According to kinematics equations, we have:

$$v_{i+1} = \sqrt{v_i^2 + 2a_i\Delta r_i} \tag{5}$$

Also, Δr_i is the displacement of each segment which in this figure is Δx. According equation (5), different acceleration values(constant) are given for each segment and obtained speed-position graph for each segment. It should be noted that the relation between the speed and the position is not linear.

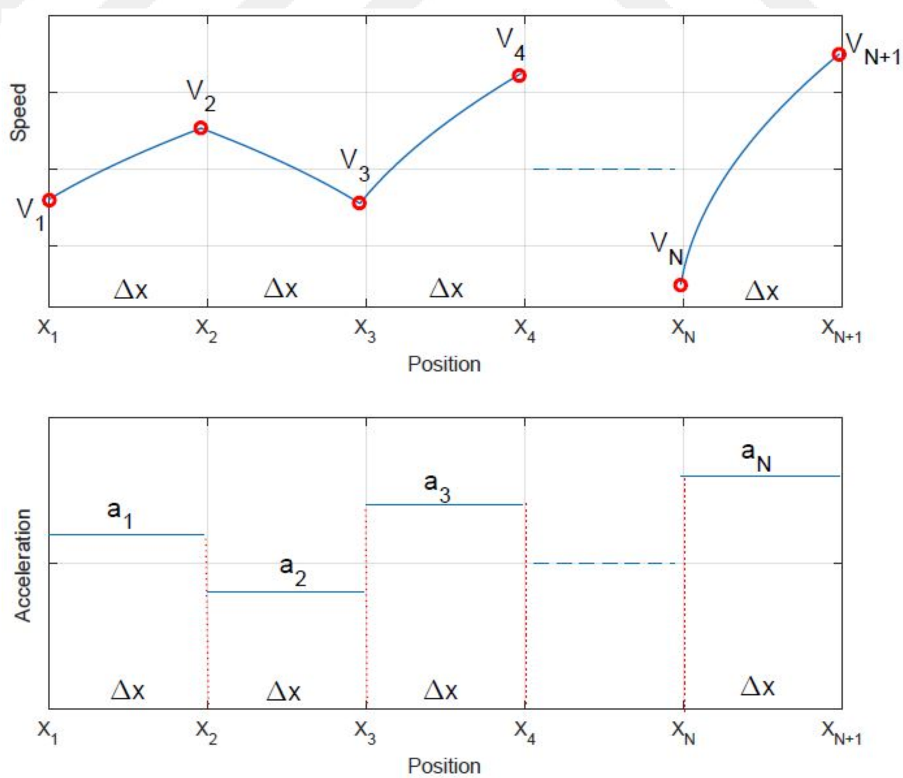

Figure 1: The speed and acceleration for a specific route

2.2 *Energy model of the system*

There is a need to define the energy consumption of vehicles under different circumstances. There are two approaches for determining the energy consumption of the vehicle. Developing the vehicle model based on physics [45, 46] or creating the statistical model based on real-world driving measurements [47, 48, 49]. Real world measurements are more realistic about energy consumption but it cannot evaluate the energy consumption for various vehicle parameters and environmental conditions. For instance, based on the effect of the weather condition on routes, some vehicle parameters may change. In this chapter, a physical model of vehicle is discussed as a function of route data which are inputs to the optimization. The required energy to attain a route is divided in to four parts:

1. Mechanical energy (kinetic and potential)
2. Energy loss due to air drag
3. Energy needed for accessories
4. energy loss due to rolling resistance

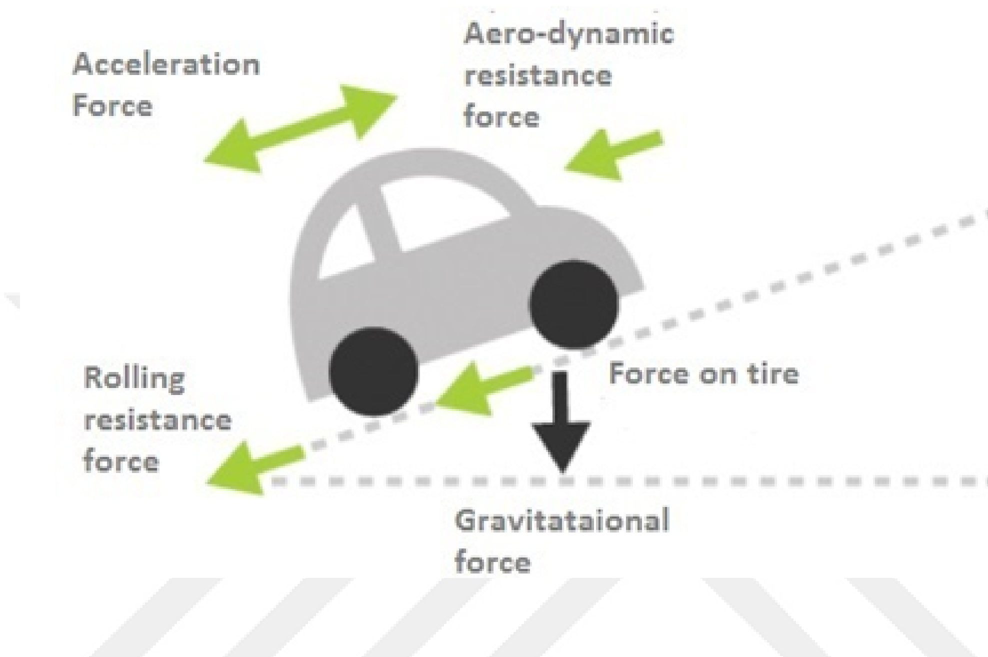

Figure 2: Forces acting on the vehicle

2.2.1 Kinetic energy

Translational and rotational kinetic energy in a specific segment can be calculated from the speed variation, the vehicle effective mass as follows:

$$\Delta K_i = K_{i+1} - K_i = \frac{1}{2} m_{\text{eff}} (v_{i+1}^2 - v_i^2) \tag{6}$$

where the vehicle effective mass is :

$$m_{\text{eff}} = m + I_{\text{motor}} \left(\frac{G_b}{R_{\text{tire}}} \right)^2 + I_{\text{tire}}. \left(\frac{1}{R_{\text{tire}}} \right)^2 \tag{7}$$

- m : Gross mass of the vehicle
- I_{motor} : Moment of inertia of motor
- I_{tire} : Combined moment of inertia of four tires

- G_b : Gear ratio ($\frac{W}{W_{\text{tire}}}$)
- R_{tire} : Radius of tire

2.2.2 Potential energy

The potential energy due to change in elevation for a specific segment can be expressed by:

$$\Delta U_i = U_{i+1} - U_i = mg(h_{i+1} - h_i) \tag{8}$$

Thus, this is well defined for the given route which includes the elevation information.

2.2.3 Aerodynamic work

The aerodynamic shape of PEV directly affects the energy due to the air drag. Furthermore, the wind speed and direction are other factors in aerodynamic work which are ignored in this thesis. The force due to air drag (F_{drag}) can be calculated by the following equation:

$$F_{\text{drag}} = \frac{1}{2}\rho A c v^2 = k_{\text{drag}} v^2 \tag{9}$$

where k_{drag} is defined to simplify the expressions.

$$k_{\text{drag}} \equiv \frac{1}{2}\rho A c$$

ρ : air density

A : cross section area

c : aerodynamic drag coefficient(depends on design)

The average modern automobile achieves a drag coefficient of between 0.25 and 0.3. Reported drag areas range from 0.47 m^2 to 2.46 m^2. The energy needed to overcome the air drag in segment-i can be calculate as follows:

$$W = \int F.dr = \int k_{\text{drag}} v^2.dr \tag{10}$$

Using $v = \frac{dr}{dt}$,

$$W = \int k_{\text{drag}} v^3 . dt \tag{11}$$

And using $a = \frac{dv}{dt}$ which is constant in each segment, we will have:

$$W = \int \frac{k_{\text{drag}} v^3 . dv}{a} \tag{12}$$

And using equation (4), we have:

$$W = \Delta E_{\text{drag}} = \frac{k_{\text{drag}} . \Delta r}{2} (v_{i+1}^2 + v_i^2) \tag{13}$$

2.2.4 Power for accessories

Usually, only up to about 2% of a vehicle's total power has consumed by powering accessories (Lights, AC, heater, etc). The energy needed for accessories can be expressed by the following equation:

$$\Delta E_{Acc,i} = P_{\text{Acc}} . \Delta t_i \tag{14}$$

Although, this expression seems simple, Δt_i is not constant. Using equation (3) it can be written:

$$\Delta E_{Acc,i} = \frac{2 P_{\text{Acc}} . \Delta x}{v_i + v_{i+1}} \tag{15}$$

2.2.5 Rolling resistance work

The rolling resistance work can be calculate based on the rolling resistance coefficient of the tires which depends on four factors [36]:

(1) tire design

(2) tire pressure

(3) road surface characteristics

(4) tread conditions

The rolling resistance force (F_{rolling}) can be expressed by the following equation:

$$F_{\text{rolling}} = C_{\text{rolling}}.N \tag{16}$$

where

$$N = mg\cos(\theta) \tag{17}$$

m : mass of the vehicle

g : Gravitational acceleration

C_{rolling} : Coefficient for rolling resistance

Note that the route data can be converted to Δh , Δr . Then, energy Loss due to rolling resistance can be calculated by the following equation:

$$\Delta E_{\text{rolling}} = F_{\text{rolling}}.\Delta r = C_{\text{rolling}} mg.\frac{\sqrt{dr^2 - dh^2}}{\Delta r}.\Delta r = C_{\text{rolling}} mg.\sqrt{\Delta r^2 - \Delta h^2} \tag{18}$$

2.2.6 Regenerative braking (RB)

A dynamic or quasi-static approach is used to model the energy consumption of BEV [60, 61]. The dynamic approach, which its inputs are a function of time, requires high computational effort and describes the driving process of the vehicle accurately. In quasi-static approach using algebraic equations, the vehicle driving speed, acceleration, and route data are the model inputs and the energy consumption of the battery is the model output [51]. Since the motor and the inverter is not perfectly efficient, an efficiency variable must be introduced in electric vehicle model which depends on RPM and torque.

Regenerative braking (RB) is one method which converts the mechanical energy from the motor into electrical energy and fed back into the battery source for recharging. In RB mode, when the driver applies a force to the brake pedal, the car starts to slow down and the electric motor operates as a generator and recharges the battery with some less than total efficiency. The RB system is useful for stop-and-go traffic. RB has to be used in conjunction with friction braking for safety reasons [61, 62]:

1. For RB a traditional friction based braking is necessary as a backup.

2. RB is not useful at low speeds and may fail to stop the vehicle.

3. RB can be only applied when the battery is not fully charged.

4. The motor cannot fully recover the energy if the braking power is huge in the emergency situation.

Two problems need to be solved in the design of brake system for EVs. Firstly, the braking force has to be applied properly to slow the vehicle while guaranteeing the stability of the vehicle; secondly, recover as much energy as possible to improve the overall efficiency [63]. Many researchers warn on the design of regenerative braking have focused on the development of control techniques and make cooperation between regenerative and friction braking [61, 64, 65]. This thesis did not discuss the control of regenerative braking. The total energy consumption with consideration of driving efficiency and regenerative braking efficiency can be formulated by the following:

ΔE= energy taken from the battery to provide torque to generate mechanical energy +non-mechanical energy (energy for accessories)

$$\Delta E_i = (\Delta K_i + \Delta P_i + \Delta E_{\text{drag}} + \Delta E_{\text{rolling}}).C + \Delta E_{Acc,i} = \Delta E_{M.E,i}.C + \Delta E_{Acc,i} \quad (19)$$

$$C = \epsilon_{regen}.\epsilon_{\text{system}} + \left(\frac{1}{\epsilon_{\text{system}}} - \epsilon_{\text{regen}}.\epsilon_{\text{system}}\right).u(\Delta E_{\text{M.E},i}) \quad (20)$$

ϵ_{system} : driving efficiency

ϵ_{regen} : regenerative braking efficiency

$dE_{\text{M.E},i}$: the mechanical energy for each segment

Thus, when $\Delta E_{\text{M.E},i}$ is positive, energy received from battery is:

$$\Delta E_i = \frac{\Delta E_{\text{M.E},i}}{\epsilon_{\text{system}}} + \Delta E_{\text{Acc},i} \quad (21)$$

However, when, $\Delta E_{\mathrm{M.E},i}$ is negative, the energy stored to the battery is

$$-\Delta E_i = -\epsilon_{regen}.\epsilon_{\mathrm{system}}\Delta E_{\mathrm{M.E},i} - \Delta E_{Acc,i} \tag{22}$$

Furthermore, the relationship between rotation of speed and speed of vehicle can be calculated by the following equation:

$$\omega_{\mathrm{tire}} = \frac{v}{R_{\mathrm{tire}}} \quad , \quad \omega = \omega_{\mathrm{tire}}.G_b \quad , \quad P = \tau\omega \tag{23}$$

where

R_{tire}: radius of tire

v : speed of vehicle

ω_{tire} : Angular velocity of tire

ω : Angular velocity of motor

τ : Torque provided by electric motor

G_b : Gear ratio

Using equation (16) and equation (17) the torque and rotation speed for each segment can be extracted by the following equations:

$$\omega_i = \frac{v_i}{R_{\mathrm{tire}}} \tag{24}$$

$$\tau_i = \frac{R_{\mathrm{tire}}}{v_i}\frac{\Delta E_{ME,i}}{\Delta t_i} \tag{25}$$

Once the torque and average-angular velocity for each segment is calculated, then the efficiency can be extracted in each segment using the efficiency-map.

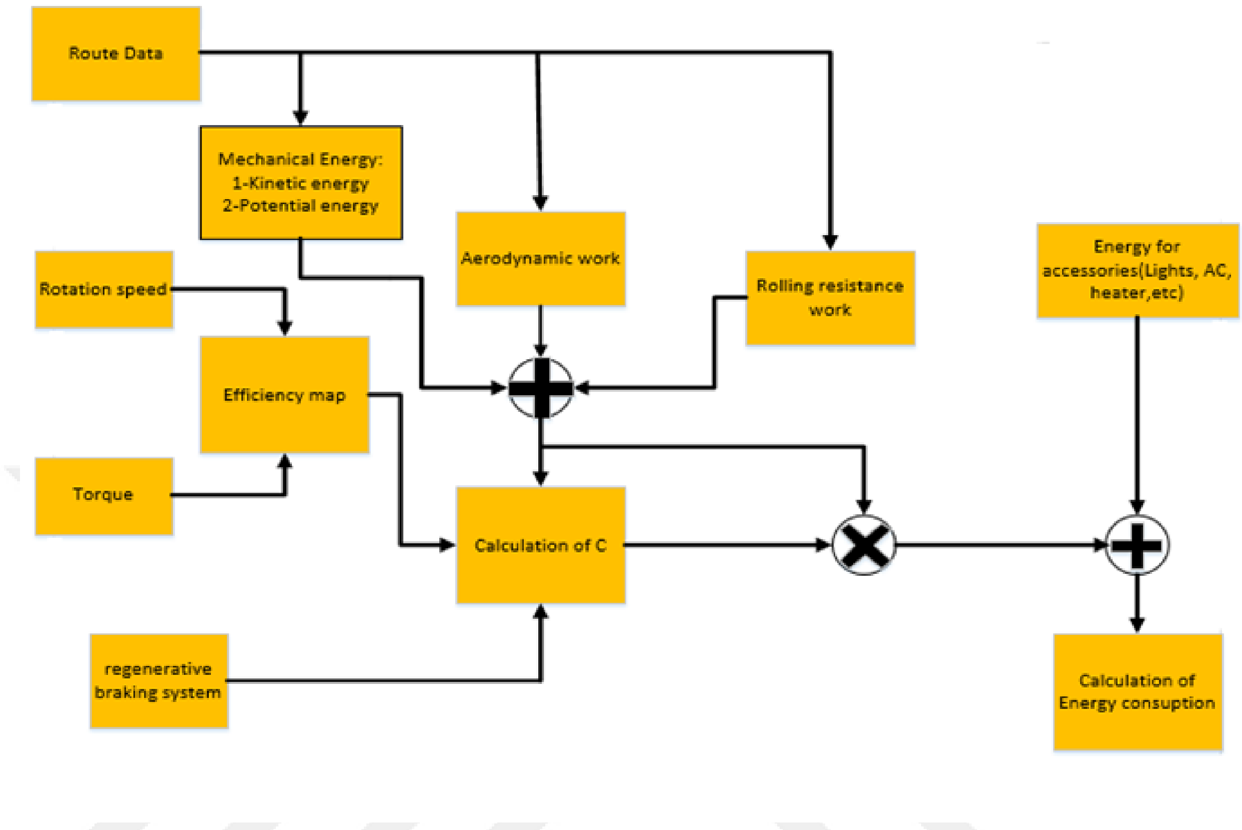

Figure 3: Overview of the whole procedure for energy consumption calculation

2.2.7 Representation of the route

In this part, the road data coordinates (x, y, z) and the distance between two points are calculated through the data provided by Google Map information (longitude, latitude, and altitude). Given the polar coordinates of a point p= (longitude, latitude, altitude) as Figure 4 show, the equivalent Cartesian coordinates (x, y, z) can be calculated.

$$x' = (R_{\text{earth}} + \text{altitude}).\cos(\text{latitude}).\cos(\text{longitude}) \tag{26}$$

$$y' = (R_{\text{earth}} + \text{altitude}).\cos(\text{latitude}).\sin(\text{longitude}) \tag{27}$$

$$z' = (R_{\text{earth}} + \text{altitude}).\sin(\text{latitude}) \tag{28}$$

Rotation around z axis and y axis:

$$T_z = \begin{bmatrix} \cos\phi & \sin\phi & 0 \\ -\sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{29}$$

$$T_y = \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix} \tag{30}$$

where

$$\theta = \arccos\left(\frac{z}{R_{\text{earth}} + \text{altitude}}\right) \tag{31}$$

$$\phi = \arccos\left(\frac{z}{(R_{\text{earth}} + \text{altitude}).\cos(\text{altitude})}\right) \tag{32}$$

$$\text{Transform} = T_z T_y \tag{33}$$

$$\text{new\_coordinate}(\text{x}, \text{y}, \text{z}) = \text{transform} * \text{old\_coordinate}(\text{x}', \text{y}', \text{z}') \tag{34}$$

$$\text{total\_distance} = \sqrt[2]{\Delta x^2 + \Delta y^2 + \Delta z^2} \tag{35}$$

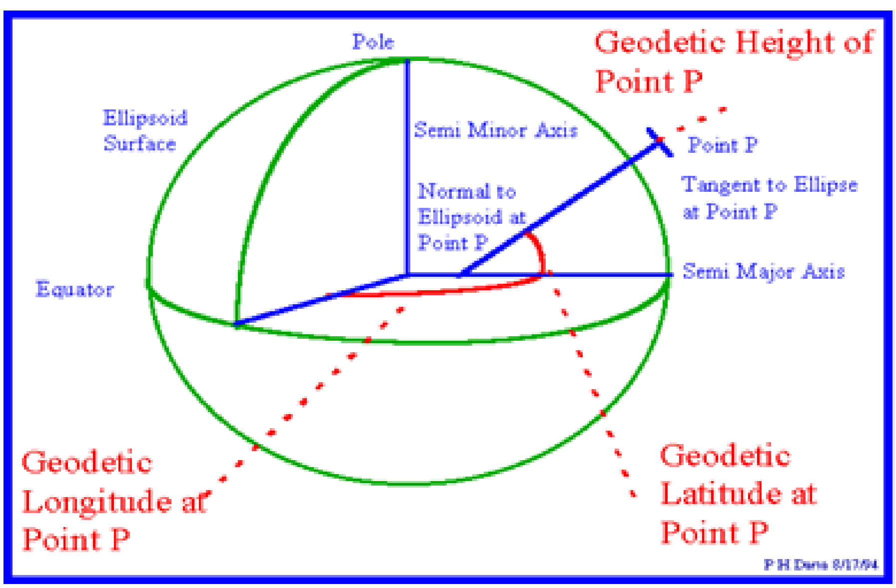

Figure 4: longitude, latitude, and altitude of earth[50]

Thus (x,y,z) yields the location in Cartesian coordinate and +x is east, such that +y is north and +z is elevation above R_{earth}.

2.2.8 Energy optimization

Different speed profiles, which lead to different energy consumption, are possible for a route. To determine the minimum energy consumption of EV, an optimal speed should be obtained. For the optimal speed driving, the driving speed is optimized using a minimization method to achieve minimum battery energy consumption. The speed of the vehicle at the beginning of each segment is chosen as the design variable because it is dependent on the vehicle motor output power and external resistance force. Furthermore, the acceleration in the specific time does not have any influence on the value at another time.

The optimization problem is to find the speed profile with which the net battery energy consumption is minimum. The energy extracted from the battery in a driving scenario is :

$$\Delta E_{battery} = \sum_i \Delta E_i \tag{36}$$

Where ΔE_i is defined in equation 21, which take regenerative braking into account.

2.2.9 State of charge calculation

A battery is an electrochemical cell that transforms chemical energy into electrical energy. The equivalent circuit of the battery is composed of an internal resistance and the fixed voltageV_{batt}.The parameter V_{batt} can be calculated by two different equations [52,53,54]. If the current of the low frequency dynamic is positive, then the battery is in the discharge mode,V_{batt}=$V_{discharge}$, as shown in Eq. (3) and if the current low frequency dynamic is negative, then the battery is in the charge mode, V_{batt}=V_{charge}, as calculated in Eqs.(7) and (8).

$$V_{discharge} = V_0 - \frac{KQ_{max}}{Q_{max} - q} i^* - \frac{KQ_{max}}{Q_{max} - q} q + Ae^{-Bq} \quad (37)$$

$$V_{charge} = V_0 - \frac{KQ_{max}}{0.1 * Q_{max} - q} i^* - \frac{KQ_{max}}{Q_{max} - q} i.t + Ae^{-Bq} \quad (38)$$

Where $Q_{max}$is the maximum capacity (Ah),V_0 is the constant voltage (v), A is the exponential voltage and B is the exponential capacity $(Ah)^{-1}$,q=it is the available capacity (Ah), and k is the polarization constant$(Ah)^{-1}$. The SOC is calculated as[55]:

$$Soc_{Batt} = 100(1 - \frac{\int i(t)dt}{Q_{max}}) \quad (39)$$

where:

$$i(t) = C.(\frac{\tau\omega}{V_{bus}}) \quad (40)$$

ω : Angular velocity(rad/sec)

τ : Torque provided by electric motor

V_{bus} : DC-bus voltage

The state of charge of the battery is bound between 0% indicate an empty battery, and 100% indicate a fully charged battery.

2.2.10 Variability of parameters

It should be noted that this is a model and calculated energy consumption depends on model parameters which determine the systematic error. The variability of the parameters is listed in Table 1. Systematic error analysis is beyond the score of this thesis. This table can be used for future work.

Table 1: Variability and dependency of vehicle longitudinal dynamic parameters

$Parameters$	$Dependency$	$Variability$
g, C_D, A	-	None
m	load	low
ρ	weather	low
C_{rolling}	road, weather	high
θ	road	high
v_{wind}	route, weather	high
a_x , v	traffic,road,driver	extremely high

CHAPTER III

OPTIMIZATION WITH MONTE CARLO METHOD

Monte Carlo method is a common name for a wide variety of stochastic techniques. These techniques are based on the use of random numbers and probability statistics to investigate problems in areas as diverse as economics, nuclear physics, and flow of traffic. We use Metropolis *et.al.* algorithm [59]. It is based on random change in the state of C_i which is chosen to be small in general iteratively, resulting in a trial state C^t_{i+1} [58].

1) if the trial state is accepted, then

$$C_{i+1} = C^t_{i+1} \tag{41}$$

2) else, when the the trial state is rejected,then

$$C_{i+1} = C_i \tag{42}$$

These state-Jumps will create a probability distribution of energies which depends on the energy of the state, favoring the lower energy states obeying the thermodynamic laws. We can define $P_A(t)$ as the probability in state A at time t and $W(A \to B)$ the transition rate from state A to the state B.This process can be described by the master equation [58]:

$$\frac{dP_A(t)}{dt} = \sum_{A \neq B} [P_B(t)W(B \to A) - P_A(t)W(A \to B)] \tag{43}$$

For every pair of states A and B, if the system reaches a state that two terms cancel one another, then it will approach to an equilibrium state. The meaning of this condition can be expressed [59]:

$$\frac{dP_A(t)}{dt} = 0 \tag{44}$$

The probability of sampling of a state A is equal to the Boltzmann weight [58].

$$P_A = \frac{e^{-\beta E_A}}{Z} \tag{45}$$

where E_A is the energy of state A and β is equal to $\frac{1}{kT}$ and Z is the partition function. Knowledge about Z is not necessary because the transition probabilities are constructed with the ratio of probabilities.

$$\frac{W(B \to A)}{W(A \to B)} = \frac{P_A}{P_B} = e^{-\beta(E_A - E_B)} \tag{46}$$

Monte-Carlo (MC) Metropolis *et.al.* algorithm in our case is according to these steps:

1. Choose multiple points, a small of them, such as $(v_i, v_j, ...)$ which (i[2,N], j[2,N], ...) to change randomly in order to speed up.Note that we exclude $i = 1$ and $i = N$ which are initial and final speeds that are constraint and are usually zero.

2. Calculate $E_{initial}$ on segment (i-1).

3. Generate a random number *rand* uniformly distributed in [0,1].

4. Change v_i by dv (a small step): In this case $dv = (\text{rand} * 2 - 1) * dv_{max}$ is chosen a small value ([-dv_{max}, dv_{max}]) randomly. (Note that dv_{max} is maximum speed change at each step)

5. Compute energy difference between the states:

$$\Delta E = E_{\text{trial}} - E_{\text{initial}} \tag{47}$$

6. Evaluate the transition probability which can be expressed by the following:

$$\rho(A \rightarrow B) = \frac{P(\text{stateB})}{P(\text{stateA})} = \frac{A.e.^{-E_{\text{trial}}}}{A.e^{-E_{\text{initial}}}} = e^{\frac{-\Delta E}{kT}} \tag{48}$$

7. Accept the trial state with probability. $\rho = e^{\frac{-\Delta E}{kT}}$ if:

$$\text{rand} < e^{\frac{-\Delta E}{kT}} \tag{49}$$

otherwise, stay at the same state.

Thus, the Metropolis *et.al* Monte-Carlo algorithm generates a new configuration B from a previous configuration A so that the transition probability $\rho(A \rightarrow B)$ satisfies the detailed balance condition.

1. If dv_{max} is too small then a large fraction of moves is accepted but the phase space is sampled slowly.

2. If dv_{max} is too large then most of the trail moves is rejected and there is little movement through the phase space, simulation takes too much time.

Thus, a proposed move that does not raise the total energy is always accepted, but a proposed move which results in higher energy is accepted with a probability that decreases exponentially with the increase of the energy difference.

kT can be described with the following equation:

$$kT = e^{\frac{log(\frac{kT_i}{kT_f})}{\text{count}-1}} \tag{50}$$

where

f: number of elements to be changed for trial state

kT_i: Initial temperature at the first step

kT_f: Final temperature when it reaches the last step (changing (cooling))

count: total number of MC steps

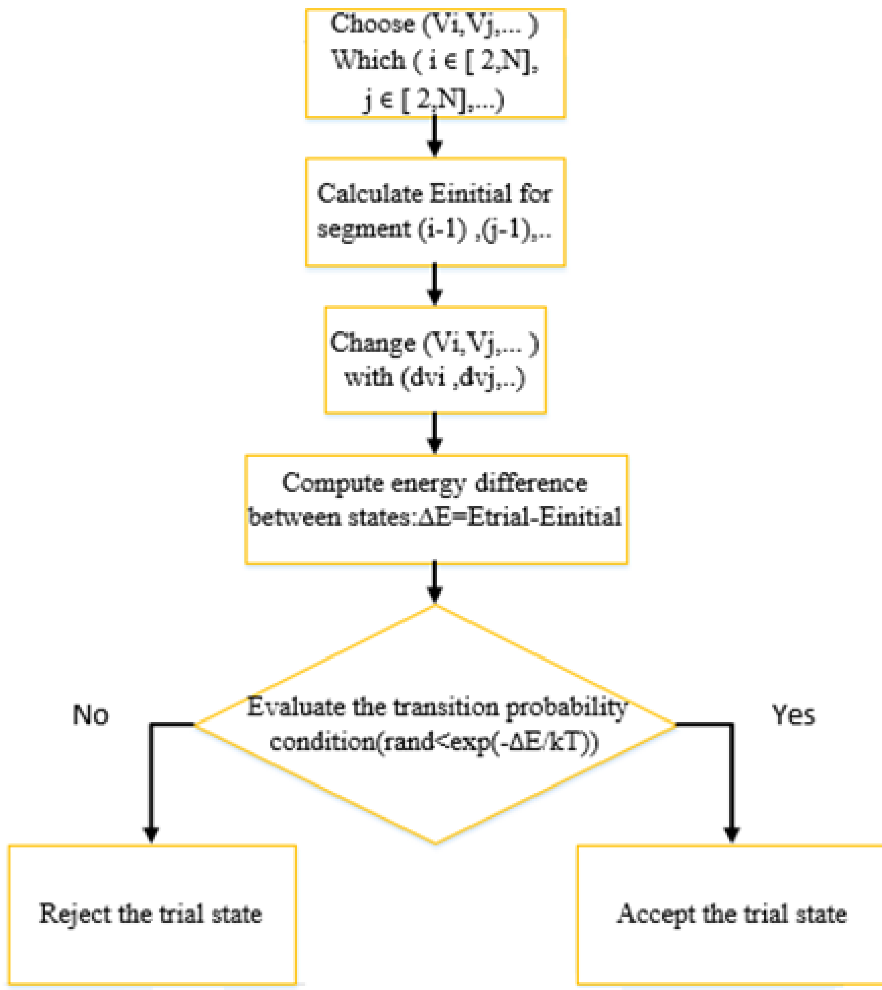

Figure 5: Flowchart of Monte-Carlo algorithm

It should be noted that T is not the physical temperature of the environment. It is merely a parameter for the Monte Carlo algorithm, which regulates the "temperature" of the probabilistic approach of the numerical model. Higher temperature, faster approach to the global minimum but the less precise answer, lower the temperature, longer approach to the minimum, but the more precise result. The variable kT_i can be regulated in order to track the optimal speed. However, the variable kT_f can be regulated in order to smooth the speed profile.

CHAPTER IV

MINIMIZATION WITH NEWTON-RAPHSON METHOD

Near-optimum of $\vec{v} = \Big[v_2, v_3, ..., v_N\Big]$ is obtained using Monte-Carlo algorithm such that the total energy is close to minima. Energy minimization is a numerical procedure for finding a local minimum on a range of speed. For example, Figure 6 can describe the local maximum and minimum. Most energy minimization methods proceed by determining the slope of the graph.

1. If the slope is positive (like point (3)) or the slope is negative(like point(1)), then points in this region is not minimum.

2. If the slop is zero (like point(2)) but the second derivative of energy function is negative, then it is local maximum energy.

3. If the slop is zero (like point(4)) but second derivative of energy function is positive, then it is local minimum energy.

Since the minimum will most likely be also a local minimum and thus a critical point, we can look at the points where $\nabla_v E(v) = 0$. . This can be done by way of Newtons method

$$\frac{\partial E(\vec{v})}{\partial v_i} = 0 \text{ for } i = 2, ..., N \tag{51}$$

Note that v_1 and v_{N+1} are constraint by the initial conditions. We will use the following definitions in our expressions:

$$E_i = \frac{\partial E(\vec{v})}{\partial v_i} \quad E_{ij} = \frac{\partial}{\partial v_i}\frac{\partial}{\partial v_j}E(\vec{v}) \quad C = \epsilon_{\text{reg}}.\epsilon_{\text{sys}} + (\frac{1}{\epsilon_{\text{sys}}} - \epsilon_{reg}.\epsilon_{\text{sys}}).u(\Delta E_{\text{M.E},i}) \tag{52}$$

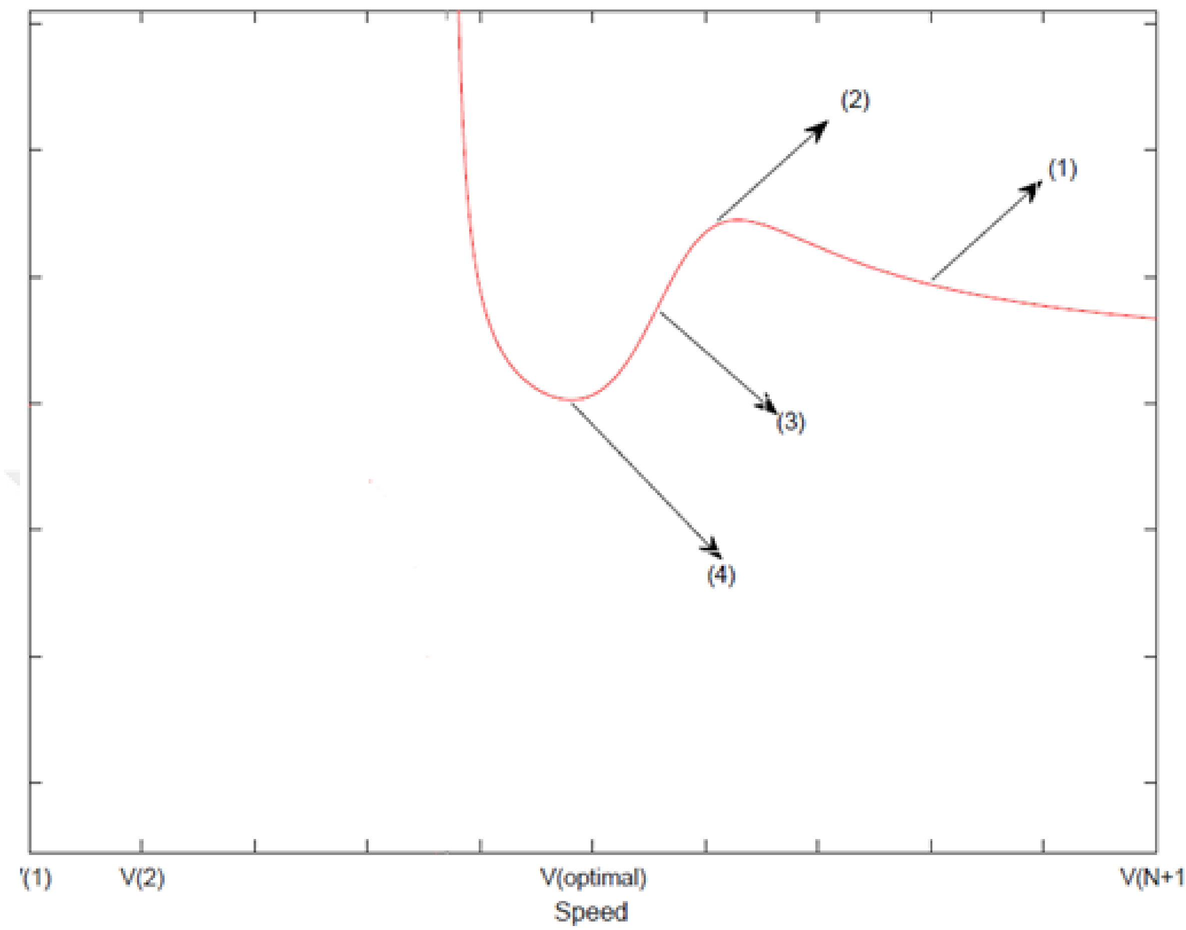

Figure 6: The process of energy changes on a range of speed.

Newton-Raphson method is based on a Taylor series expansion of the gradient energy as expressed:

$$E_i(\vec{v}) = E_i(v_0) + \sum_{j=2}^{N} \frac{\partial E_i}{\partial v_j}(v_j - v_{0j}) = 0 \tag{53}$$

Equation (30) can be simplified as a following linear matrix equations:

$$\begin{bmatrix} E_{22} & \cdots & E_{2N} \\ \vdots & \ddots & \vdots \\ E_{2N} & \cdots & E_{NN} \end{bmatrix} \begin{bmatrix} \delta v_2 \\ \vdots \\ \delta v_N \end{bmatrix} = \begin{bmatrix} -E_2 \\ \vdots \\ -E_N \end{bmatrix} \Longrightarrow \vec{M}.\delta\vec{v} = \vec{N} \Longrightarrow \delta\vec{v} = \vec{N}.\vec{M}^{-1} \tag{54}$$

Then,

$$\vec{v} = \vec{v_0} + \delta\vec{v} \tag{55}$$

Coefficients of matrix M and vector N can be extracted through following equations:

$$E(\vec{v}) = E(v_2, \cdots, v_N) = \sum_{k=1}^{N} (\Delta K_k + \Delta U_k + \Delta E_{\text{drag},k} + \Delta E_{\text{rolling},k}).C + \Delta E_{Acc,k} \tag{56}$$

E_i can be expressed as

$$E_i = \frac{\partial E(\vec{v})}{\partial v_i} = \frac{\partial}{\partial v_i} \sum_{k=1}^{N} (dK_k + dU_k + dE_{\text{drag},k} + dE_{\text{rolling},k}).C + dE_{\text{Acc},k} \tag{57}$$

Note that dE_k depends on only v_k and v_{k+1}.So, The summation terms vanishes except only $k = i - 1$ and $k = i$. So, the equation(51) is simplified as following :

$$E_i = \frac{\partial}{\partial v_i}(dE_{i-1} + dE_i) \quad i = 2, ..., N \tag{58}$$

$$E_i = \frac{\partial}{\partial v_i}([\frac{1}{2}m_{\text{eff}}(v_i^2 - v_{i-1}^2) + \frac{k_{\text{drag}}dr}{2}(v_i^2 + v_{i-1}^2)].C_{i-1} + \frac{2P_{\text{Acc}}dr}{v_i + v_{i-1}} + ([\frac{1}{2}m_{\text{eff}}(v_{i+1}^2 - v_i^2)] + \frac{k_{\text{drag}}dr}{2}(v_{i+1}^2 + v_i^2)].C_i + \frac{2P_{\text{Acc}}dr}{v_{i+1} + v_i} \tag{59}$$

Finally, E_i can be calculated through following equation:

$$E_i = m_{\text{eff}}v_i(C_{i-1} - Ci) + K_{\text{drag}}dr.v_i(C_{i-1} + C_i) - \frac{2P_{\text{Acc}}dr}{(v_i + v_{i-1})^2} - \frac{2P_{\text{Acc}}dr}{(v_{i+1} + v_i)^2} \tag{60}$$

Note that E_i depends on only v_{i+1} , v_i and v_{i-1}.So, the summation terms vanishes except only $\mathrm{j} \in \mathrm{i} - 1, \mathrm{i}, \mathrm{i} + 1$.

For $\mathrm{j} = \mathrm{i}$:

$$E_{ij} = m_{\text{eff}}(C_{i-1} - Ci) + K_{\text{drag}}dr(C_{i-1} + C_i) + \frac{4P_{\text{Acc}}dr}{(v_i + v_{i-1})^3} + \frac{4P_{\text{Acc}}dr}{(v_{i+1} + v_i)^3} \tag{61}$$

For $\mathrm{j} = \mathrm{i} - 1$:

$$E_{ij} = \frac{4P_{\text{Acc}}dr}{(v_i + v_{i-1})^3} \tag{62}$$

For $\mathrm{j} = \mathrm{i} + 1$:

$$E_{ij} = \frac{4P_{\text{Acc}}dr}{(v_{i+1} + v_i)^3} \tag{63}$$

Finally, E_{ij} can be calculated through following equation:

$$E_{ij} = m_{\text{eff}}(C_{i-1} - Ci) + K_{\text{drag}} dr(C_{i-1} + C_i) + \frac{8P_{\text{Acc}} dr}{(v_i + v_{i-1})^3} + \frac{8P_{\text{Acc}} dr}{(v_{i+1} + v_i)^3} \qquad (64)$$

After implementing Newton-Raphson method, it was found that the noise and non-analytic form of the efficiency coefficient C introduces great errors in derivatives and makes Newton-Raphson method unusable for data-driven efficiency maps as explained in Chapter 5. The efficiency map is analytically modeled and differentiable it yields the local minima extremely fast in 3-4 steps after the MC iterations. Thus, we keep this in our code as an optimal tool.

CHAPTER V

EFFICIENCY OF MOTOR-INVERTER SYSTEM

5.1 Introduction

Electric engines were discovered shortly after the invention of electricity and have been used widely even for power generation, rail systems, and heating/cooling systems. But, they have become an important topic in road vehicles very recently. The motor efficiency has become an important issue as efficiency standards increase [56]. Electric motors and the drives need to be highly efficient. A 2-D plot of efficiency is measured by engineers who design the interior permanent magnet (IPM) machines and the torque of the machine versus its rotation in the 2-D plot is called the "efficiency map" [57]. It is necessary to keep the electric motor in the highest efficiency area, which has several advantages for an electric vehicle. The most important advantages are the minimization of energy consumption from the batteries of the electric vehicle.

5.2 Preparation of lookup table

The machine efficiency map is extracted through finding the maximum efficiency for each torque and speed. We will assume a constant RPM during a segment because the efficiency data is not analytical, but merely a lookup table. Figure 7 shows the raw data of the efficiency map. A colorbar is used to specify the efficiency level. Each colored dot in the torque-speed graph represents an efficiency value. A secondary lookup table is obtained through a spline interpolation of these raw data. So, we have the function $\text{efficiency}(\text{torque}, \text{rpm})$ which return the efficiency of the system for the driving conditions using this secondary lookup table with a simple linear interpolation. Thus, it is nearly as precise as spline interpolation, but as fast as linear interpolation. Note that we should consider the limitation of the power of electric motor by multiplicity the efficiency with an exponential term which is expressed by the following equation:

$$\epsilon = \epsilon_{table} e^{(\frac{P_{max} - \omega\tau}{P_{transient}})} \tag{65}$$

Figure 8 shows the transient region of efficiency map. If the torque×speed values are greater than the maximum power, the corresponding region can be called "forbidden region". Figure 9 shows used efficiency map for our simulation which is obtained through a lookup table.

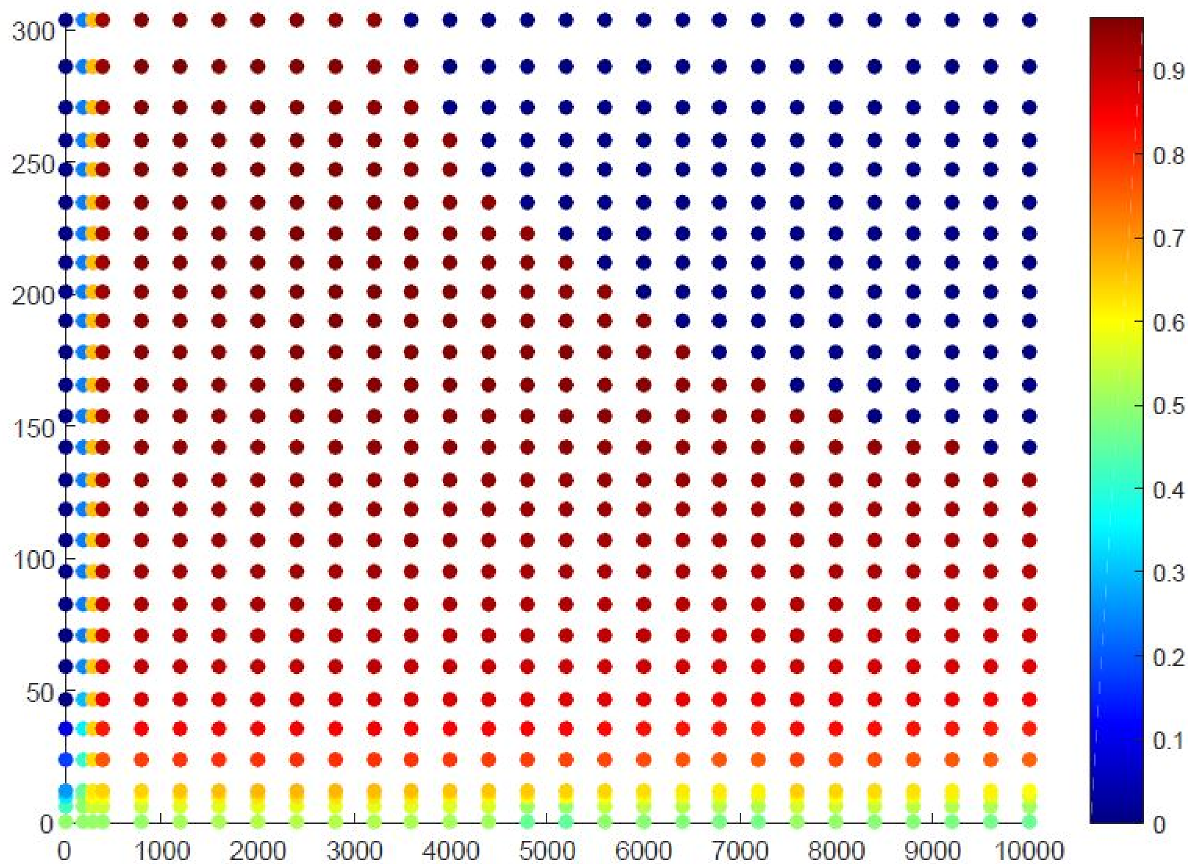

Figure 7: Raw data of Torque-Speed.

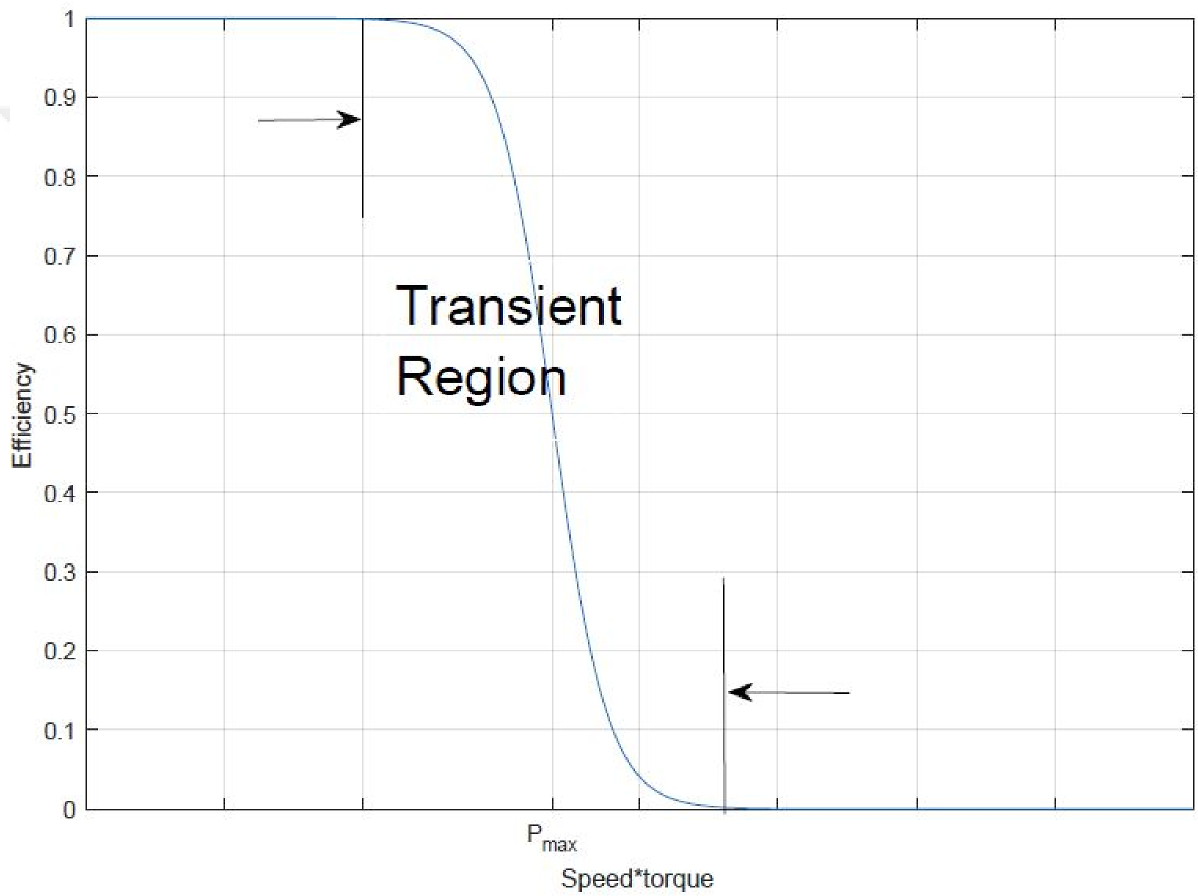

Figure 8: Transient region of efficiency map

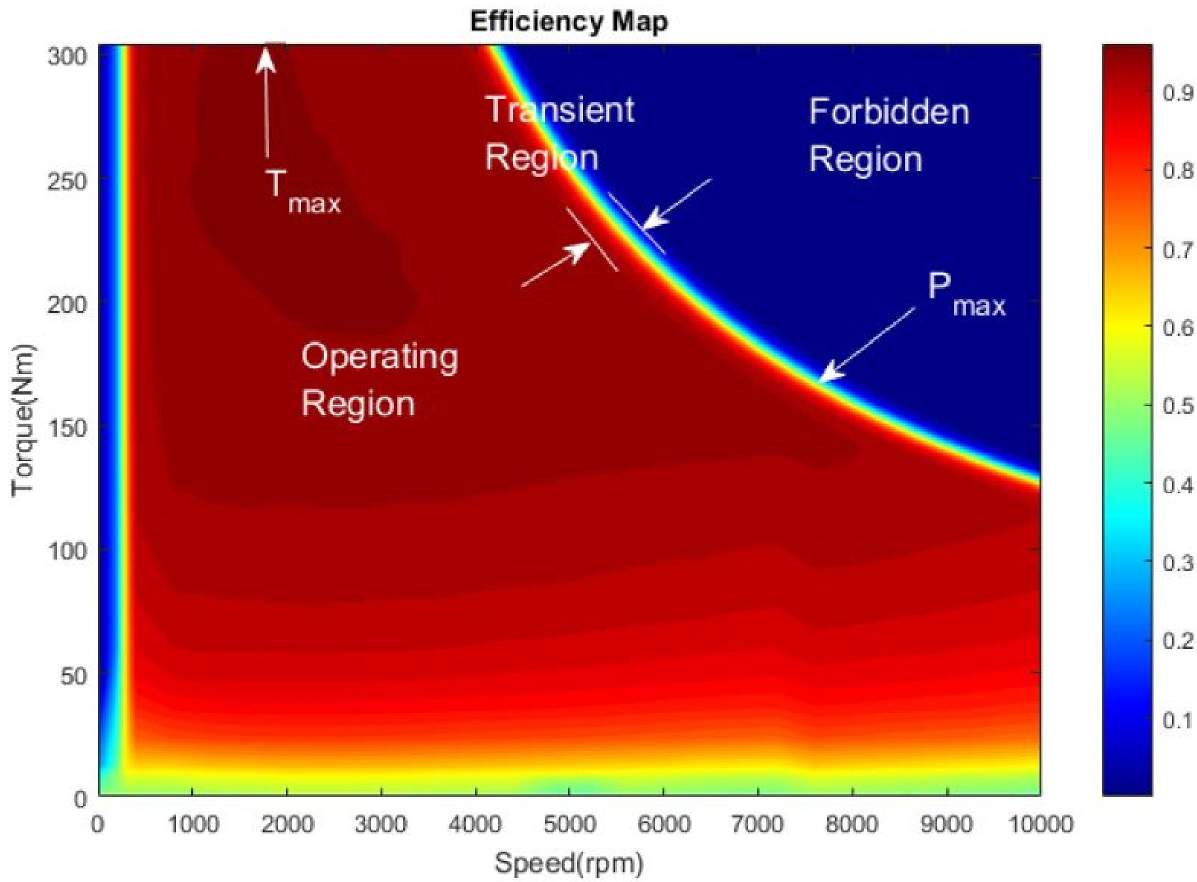

Figure 9: Spline-interpolated efficiency map.

CHAPTER VI

RESULTS

6.1 Model Parameters

In this part, the performance of the Monte Carlo (MC) method in different driving conditions are investigated. First, four different artificial scenarios including flat, uphill, downhill and uphill-downhill (a Gaussian shape) driving are chosen for testing proposes. Then, a realistic route is chosen using Google-Map and the optimization code is run to observe the outcome. MATLAB environment is used to model the electric vehicle and implement the Monte-Carlo method. The cross-sectional area and the mass of the vehicle we used are larger than a regular passenger vehicle. So, the optimal speed profile is expected to be low. Parameters of the vehicle model are taken from Hexagon Studio's electric vehicle. This company produces original design and engineering solutions on national and international scale in the sectors of transportation, defense industry, marine, agricultural machines. The capacity of battery is set to be 66 kWh for all of scenarios.

Figure 10: Karsan electric vehicle provided by Hexagon Studio.

Table 2: Parameters of the vehicle model.

Symbol	Value	Unit	Description
R	0.347	m	Effective radius of tire
g	9.80665	$\mathrm{m/s^2}$	Gravitational constant
C_{rolling}	0.008	-	Coefficient of rolling friction
c	1.7181	-	Coefficient of air drag
A	5.1	$\mathrm{m^2}$	Vehicle cross sectional area
m	4200	kg	Vehicle mass
I	0.18	$\mathrm{kg.m^2}$	Motor moment of inertia
G_{b}	18.5	-	Total gear ratio
P_{acc}	200	W	Estimated power for accessories
E_{battery}	66	kWh	Battery capacity
V_{bus}	402	V	Battery bus voltage
$\epsilon_{\mathrm{regen}}$	0.85	-	Regenerative braking efficiency

6.2 Optimizer Parameters

In this section, optimizer parameters used for Monte Carlo optimization method are described in below:

- V_{initial}: The constant initial speed used as a default value in the code. Note that different initial speed should be converged to unique average speed profile and this has been tested and confirmed, and initial and final point speeds are constrains and set to be zero.

- L_{sub} : The length of each sub-routes. The route is divided into shorter sub-routes according to this parameter.

- OR_{sub} : Overlap ratio is used as a parameter to determine the overlap between sub-routes. This parameter avoids any abruptly changes at the end of a sub-routes of speed profile.

- $T_{i,sub}^{\text{scale}}$: This parameter specifies the initial temperature used in MC.

- $T_{f,sub}^{\text{scale}}$: This parameter specifies the final temperature used in MC. Note that $T_{f,sub}^{\text{scale}} < T_{i,sub}^{\text{scale}}$ which introduces a gradual cooling during MC.

- T_i^{scale} : This parameter specifies the initial temperature of total route after collecting sub-routes.

- T_f^{scale} : This parameter specifies the final temperature of total route after collecting sub-routes.

- $\Delta r_{\text{max,sub}}$: This parameter determines the number of halving in each sub-segments such that $\max(\Delta r_i) < \Delta r_{\text{max,sub}}$ (The total path is divided into N segments and the length of each segment is Δr_i).

- $\Delta r_{\max}$: This parameter determines the number of halving of total route such that $\max(\Delta r_i) < \Delta r_{\max}$ (The total path is divided into N segments and the length of each segment is Δr_i).

- $a_{\min}$: This parameter specifies the maximum deceleration of the vehicle. The trial state will be rejected if the acceleration is less than this limit. This is set for the comfort of the passengers to avoid sudden ghost forces.

- $a_{\max}$: This parameter specifies the maximum acceleration of the vehicle. The trial state will be rejected if the acceleration is greater than this limit. This is set for the comfort of the passenger to avoid sudden ghost forces.

- $\Delta v_{\max}$: This parameter is maximum value of Δv which is chosen randomly between $-\Delta v_{\max}$ and $+\Delta v_{\max}$. Δv is, then, adjusted adaptively according to fluctuation of the MC steps.

- $N_{\text{iters/sample,MC,sub}}$: This parameter specifies the number of MC iteration per sample for each sub-routes.

- $N_{\text{iters/sample,MC}}$: This parameter specifies the number MC iteration per sample of the total route after collecting subsegments.

- $AR_{\min}$: MC loop breaks when the acceptance ratio is less than this limit.

- $\sigma^{\Delta v}_{\min}$: This parameter specifies MC loop breaks when $\sigma^{\Delta v}$ is less than this limit.

The optimizer parameters used for the test routes reported in the following section can be seen in Table 3.

Table 3: Optimizer parameters used for test routes.

Parameters	Value	Unit	Description
V_{initial}	10	km/h	Initial constant speed profile.
L_{sub}	500	m	Length of sub-routes.
OR_{sub}	0.4	-	Overlap ratio of the sub-routes.
$T_{i,seg}^{\text{scale}}$	1000	-	Initial scaled temperature (sub-routes).
$T_{f,sub}^{\text{scale}}$	10^{-5}	-	Final scaled temperature (sub-routes).
T_{i}^{scale}	1000	-	Initial scaled temperature.
T_{f}^{scale}	10^{-5}	-	Final scaled temperature.
$N_{\text{iters/sample,MC,sub}}$	500	-	MC iterations per sample (sub-routes).
$N_{\text{iters/sample,MC}}$	1000	-	MC iterations per sample.
$\Delta r_{\text{max,sub}}$	4	m	max Δr (sub-routes).
Δr_{max}	4	m	max Δr.
Δv_{max}	0.8	m/s	Initial maximum Δv.
a_{min}	-0.03g	m/s^2	Limit the deceleration.
a_{max}	0.12g	m/s^2	Limit the acceleration.
AR_{min}	0.005	-	MC loop break condition 2.
$\sigma_{\text{min}}^{\Delta v}$	0.0014	m/s	MC loop break condition 1.

6.3 Test Routes

6.3.1 Flat route

In the first scenario, a flat route of 2.5 Km is simulated. Optimal speed profile was found using the MC method. The result is shown in figure 11, all the related variables are a function of time. The total energy needed for this route turns out to be 1.141 MJ or 0.3169 kWh which is quite efficient for this size of a vehicle. In one examination of the speed profile, an interesting result immediately noticed. It is assumed that for a route, the optimization should find an optimal constant speed and complete the route with that speed, except the initial and final points chosen to be zero. However, it is observed that the vehicle speed up with moderate torque, and slow down with zero torque in periods of about 2 minutes. Because it was found out that the efficiency is higher at moderate torque, then a low torque region (see Figure 9), then rather than a continuous low-efficiency operator, it prefers to have the high efficiency operations and optimizing the total energy consumption. This is an interesting result for such a simple route.

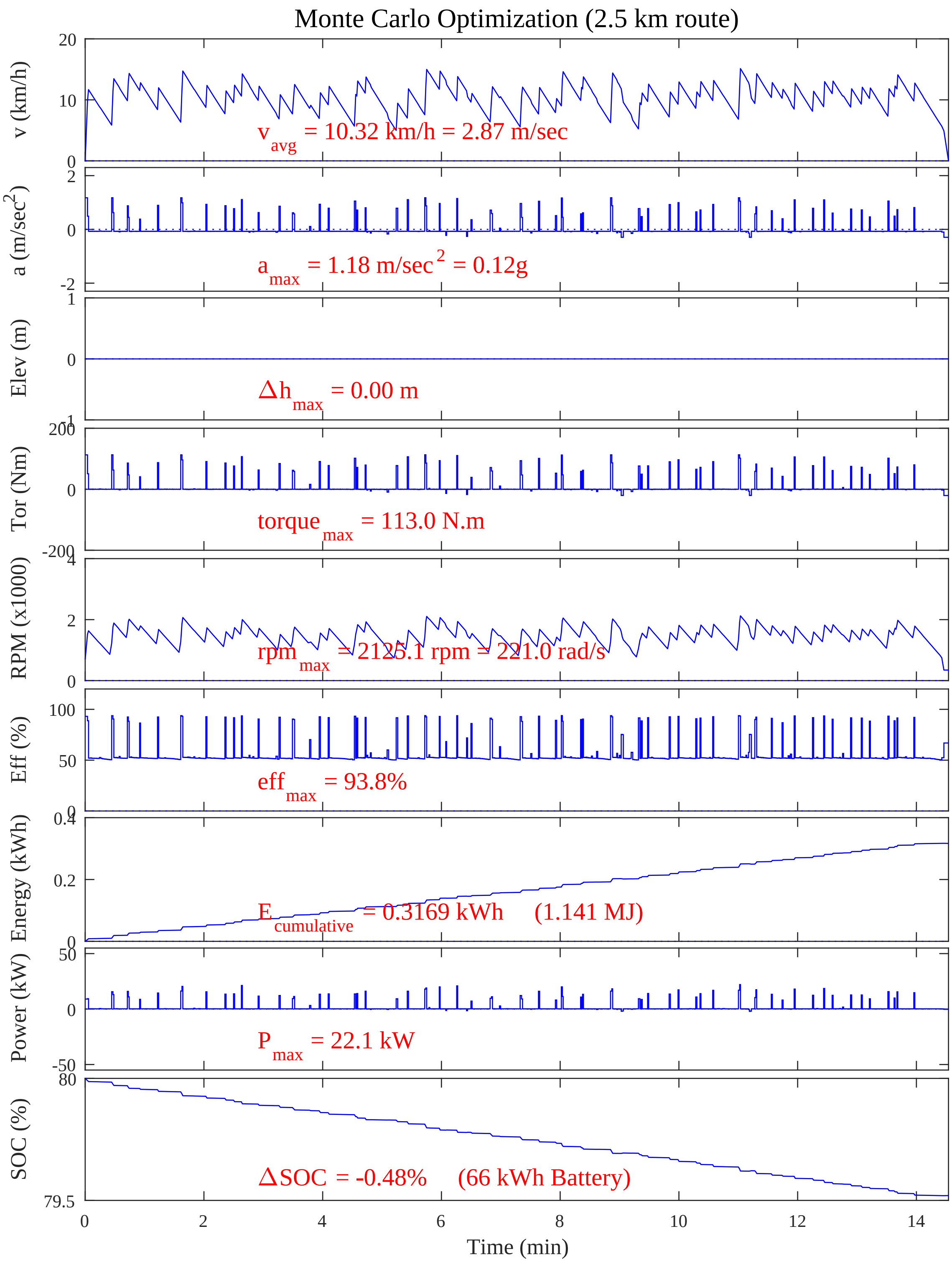

Figure 11: Simulation results of the vehicle speed, acceleration, torque, angular speed, efficiency, energy consumption, power and state of charge in an flat route.

6.3.2 Uphill route

In the second scenario, uphill routes are considered. Figure 12 and Figure 13 show the behavior of the vehicle in 5% grade and 10% grade. Using the MC method, energy consumption for a 10% grade is decreased to 6.99 MJ (1.93 kWh) and for 5% grade is decreased to 12.17 MJ (3.38 kWh). In this scenario, torque has been moderate at all times and also efficiency is very high. Thus, speed up-cruise-down cycles were not necessary to optimize the efficiency as they were for the flat-route case.

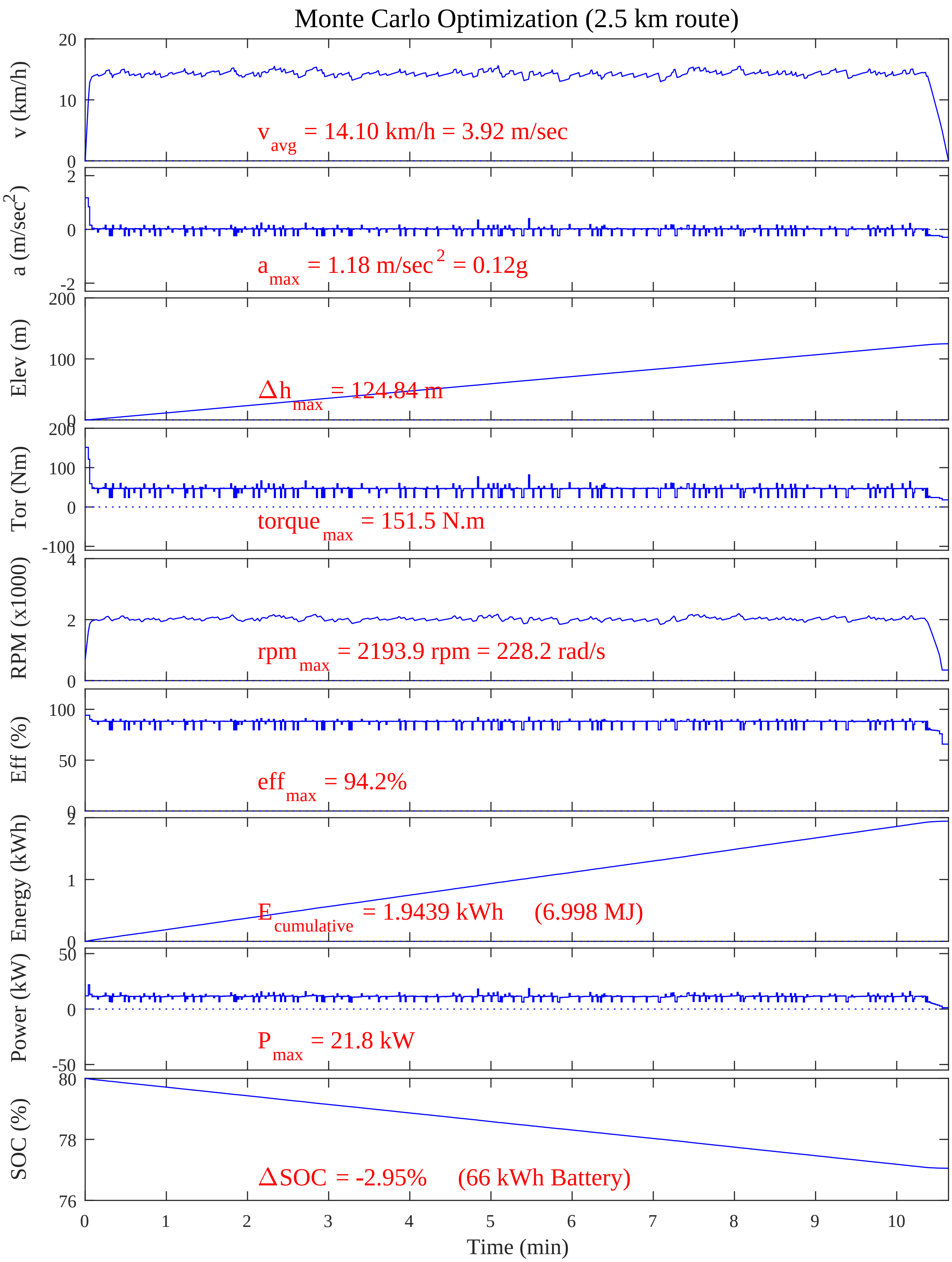

Figure 12: Simulation results of the vehicle speed, acceleration, torque, angular speed, efficiency, energy consumption, power and state of charge in an 5% slop uphill route.

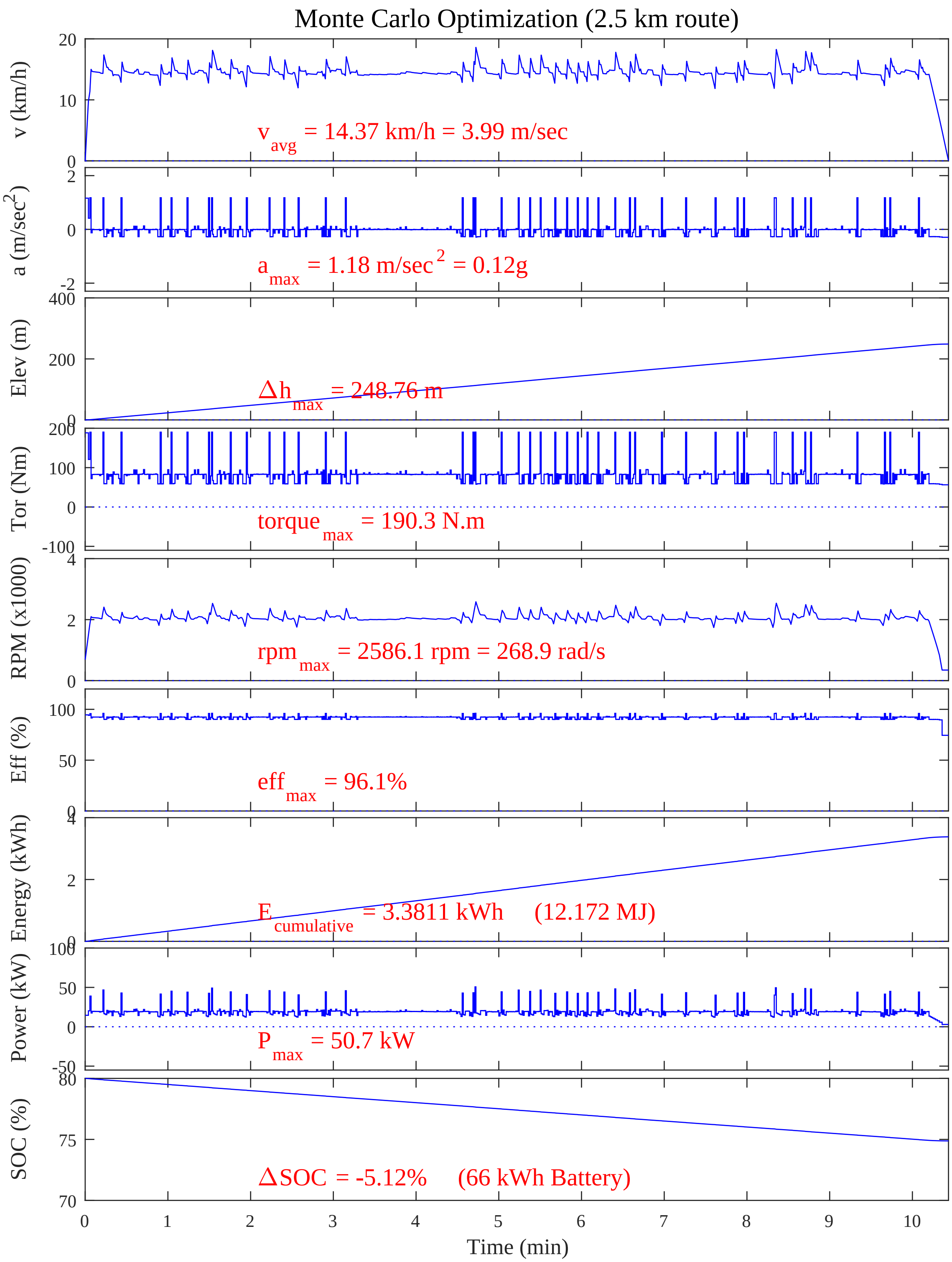

Figure 13: Simulation results of the vehicle speed, acceleration, torque, angular speed, efficiency, energy consumption, power and state of charge in an 10% grade uphill route.

6.3.3 Downhill routes

In the third scenario, a downhill route is considered. Figure 14 and Figure 15 show the behavior of the vehicle in -5% grade and -10% grade. In this scenario, the electric motor operates as a generator and charge the battery. Optimization achieves this by finding a speed profile such that the gravitational pull is larger than various resistance forces in the model. However, due to the slow process of recharging the state of charge will be increased just slightly. At lower speed, the charging kicks in strongly when it crosses a certain level, thus we again see a sawtooth like a shape in speed profile to optimize the charging at high efficiency region. This requires a control unit for the battery pack to efficiently use regenerative braking.

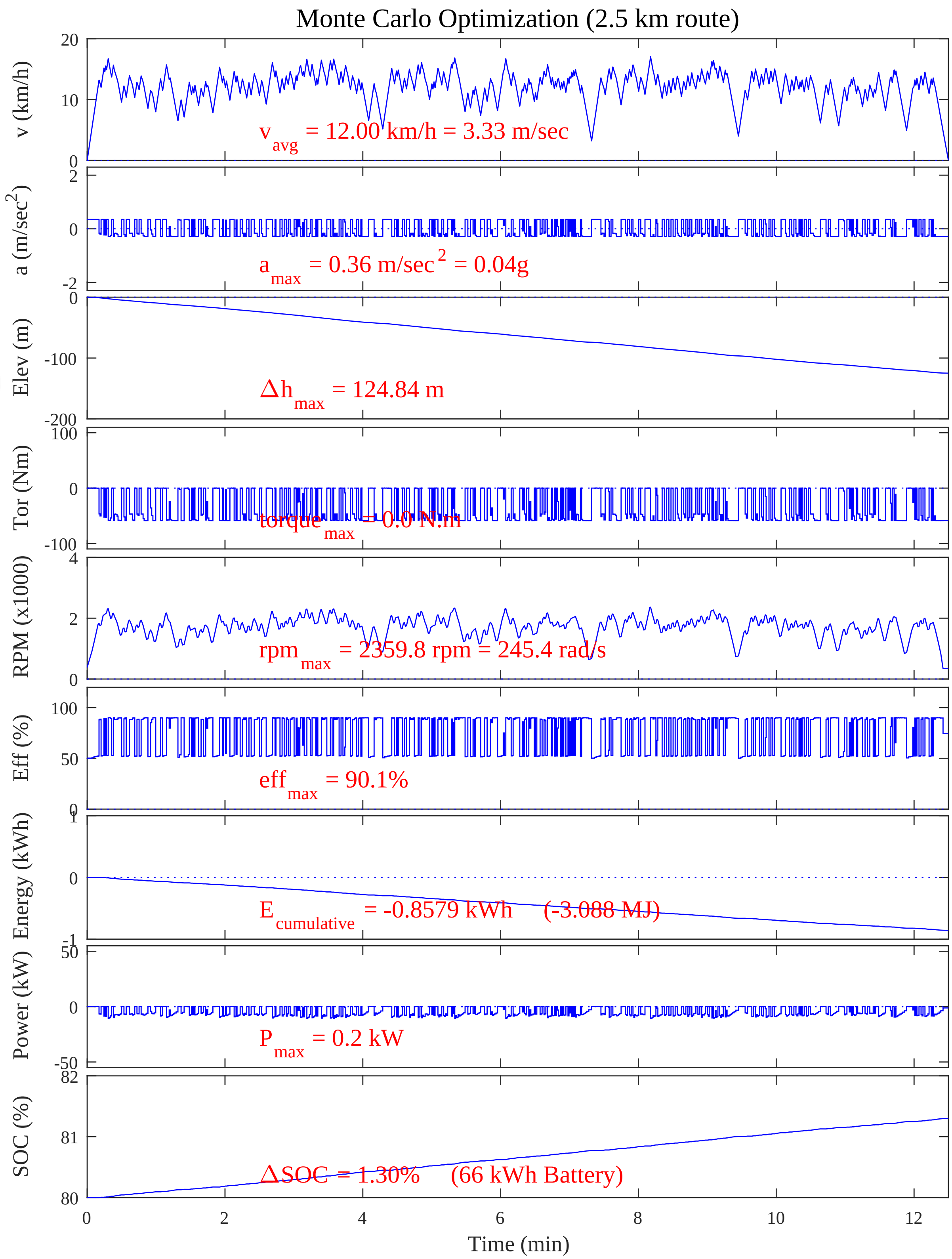

Figure 14: Simulation results of the vehicle speed, acceleration, torque, angular speed, efficiency, energy consumption, power and state of charge in an -5% grade downhill route.

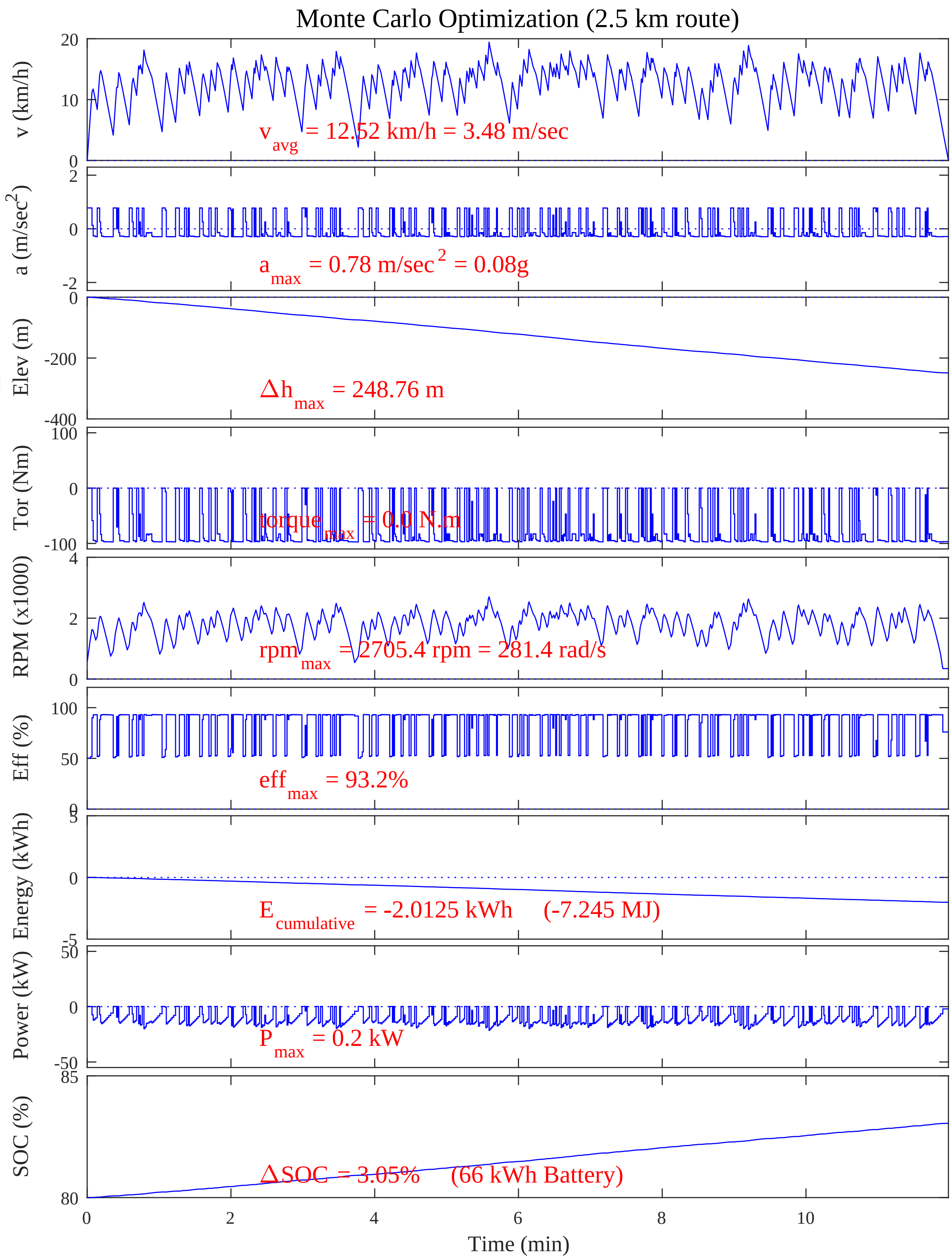

Figure 15: Simulation results of the vehicle speed, acceleration, torque, angular speed, efficiency, energy consumption, power and state of charge in an -10% grade downhill route.

6.3.4 Uphill-Downhill route

In the last test scenario, a route with a Gaussian distribution is considered. In this case, the energy consumption is found at 2.07 MJ (0.57 kWh) by the MC method. As the vehicle moves on the uphill, the torque is positive, thus energy is consumed and as it moves downhill, the torque is negative, this regenerative system charges the battery. Furthermore, as the vehicle moves toward a top point in the Gaussian route, the speed of the vehicle is decreasing (the kinetic energy is converted to potential energy) and as the vehicle moves from top of the hill to the flat region, the potential energy is converted to kinetic energy, thats why the speed is increasing. It should be noted that the total energy consumption is increased by 81% compared to a flat route. This figure could be higher due to climbing up if regenerative braking would be missing.

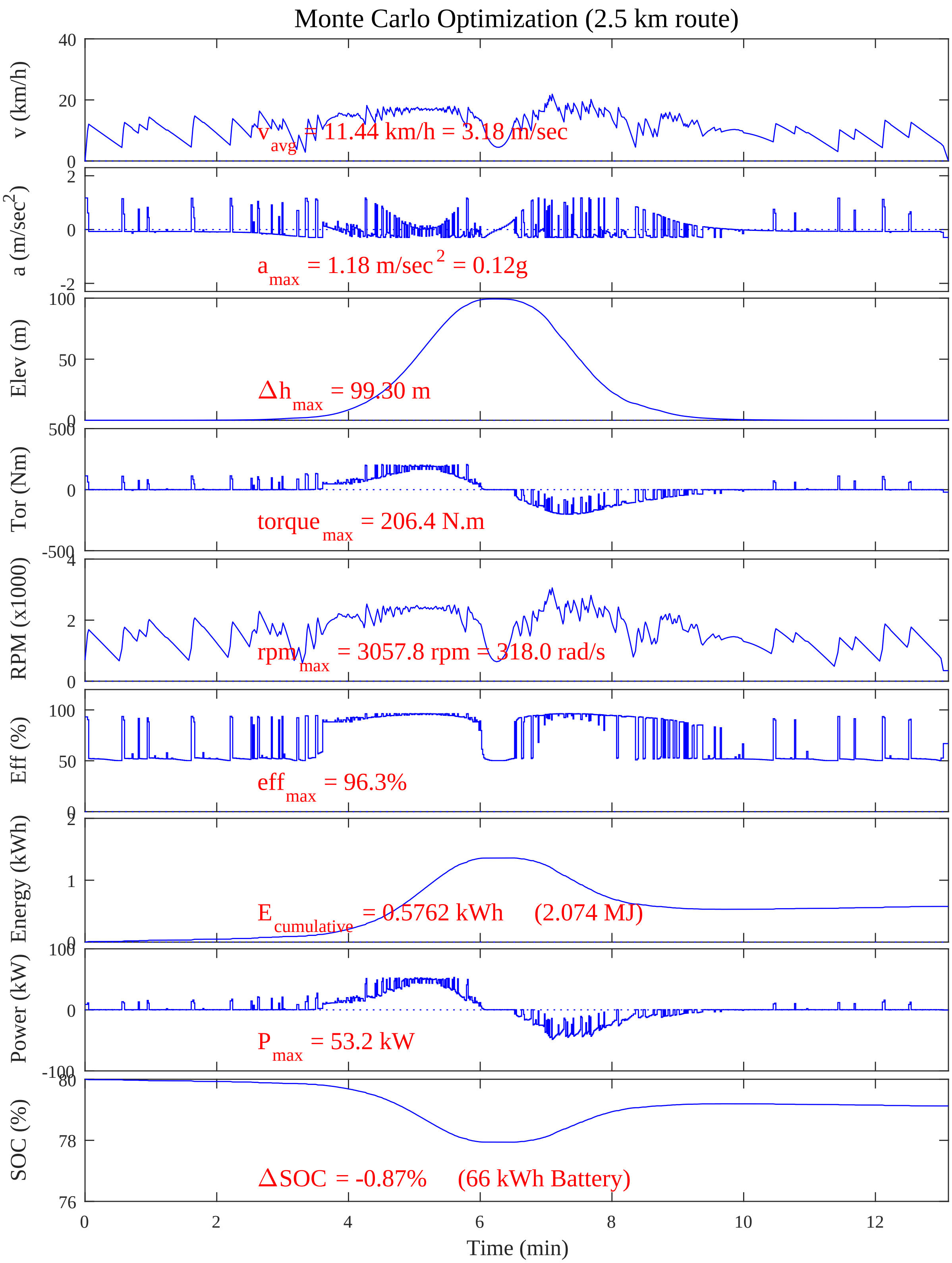

Figure 16: Simulation results of the vehicle speed, acceleration, torque, angular speed, efficiency, energy consumption, power and state of charge in an uphill-downhill route.

6.4 Realistic route

To verify the accuracy of the proposed method, a specific route as shown in figure 17 is considered. The route data including longitude, latitude, and the altitude is extracted from Google map. Figure 18 shows the performance of the MC method in a specified route with an initial speed of 10 km/h. Using MC method the speed level is decreased to converge the optimal speed profile in order to minimize the energy consumption. The energy consumption at the destination is found by MC method to be 0.502 MJ (0.139 kWh).

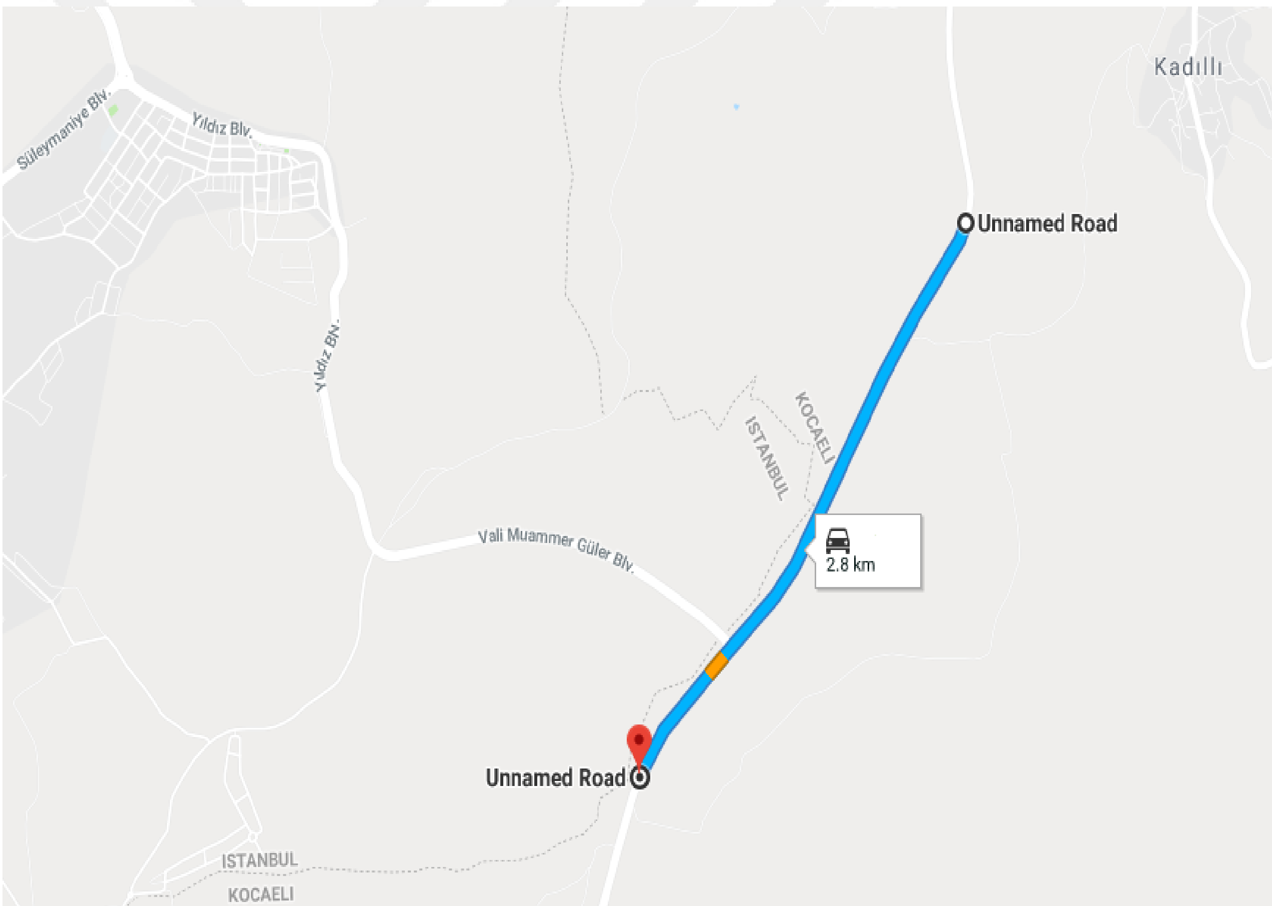

Figure 17: Test route extracted from Google Map

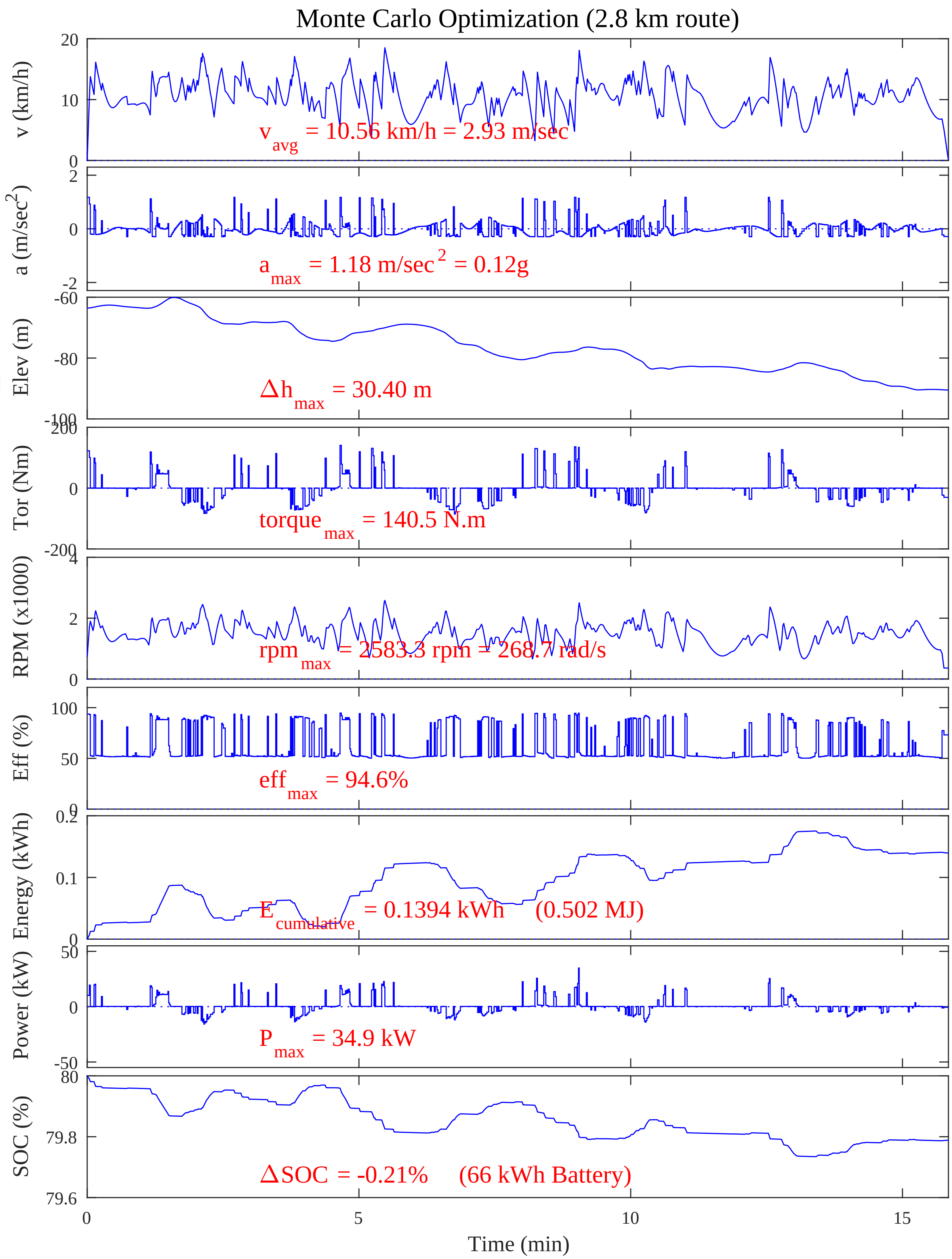

Figure 18: Simulation results of the vehicle speed, acceleration, torque and efficiency for route data. Initial speed=10 km/h.

CHAPTER VII

CONCLUSION

The goal of this thesis is to analyze, model, and optimize the energy consumption of Plug-in Electric vehicles (PEVs) in order to extend the driving range. Based on this objective, three topics were investigated:

1. Modeling of energy consumption of electric vehicle and calculation of the energy consumption of vehicle based on a given speed profile.

2. Testing the method on several routes to verify the minimization and to observe the general behavior of such a nonlinear system.

3. Finding the optimal speed profile for a chosen route in order to minimize the energy consumption of the electric vehicle.

Monte Carlo and Newton-Raphson optimization methods were used to find the optimal speed profile in order to minimize the energy consumption. The influence of road type, regenerative braking, the efficiency of battery and road slope were taken into account to calculate the energy consumption. Analysis of energy consumption of EV was tested on different types of test routes and then on a realistic route data (longitude, latitude, and altitude). Finally, the realistic route data is extracted from Google Map. The optimization was performed for an initial speed of 10 km/h, and a realistic route of 2.8 km. It yielded consistent results in each of these cases.

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