

Application of an Optimal Control Problem to a Trip-Based Energy Management for Electric Vehicles

Thomas Juergen Boehme, Florian Held, Christoph Rollinger, Heiko Rabba and
Matthias Schultalbers
IAV Automotive Engineering

Bernhard Lampe
University of Rostock

ABSTRACT

A trip-based energy management strategy for electric vehicles (EVs) is proposed. It can use deterministic routing information obtained from, nowadays, available navigation systems and determines stochastic descriptions of process uncertainties such as stop events as unpredictable disturbances. A dynamic programming algorithm is used to calculate the optimal control trajectories required to reach the target destination safely and to suggest the driver an optimal driving style to maximize the battery range. The algorithm is implemented on a rapid prototyping platform using MATLAB/Simulink. Simulations and experimental results obtained from an EV prototype car are presented.

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INTRODUCTION

A huge electric mobility development plan has been initiated by the German Government to increase the number of electric vehicles (EVs) on German roads up to 1 million exemplars by the end of 2020 [1]. However, the possibility of abrupt stopping due to "unanticipated" exhausted battery power in a region without power grids and long charging times are still big issues for the automotive industries and their suppliers in order to convince potential customers. This paper examines, therefore, the important issue of whether the driver of an EV can reach his/her trip destination safely with the current battery status, also known as the state of charge (SoC). The consideration of energy management in today's EVs is constrained to auxiliary consumer management. This is mainly due to the lack of available degree-of-freedom (DOF), which the system provides. However, by introducing an artificial vehicle speed limit the system's trajectory can be influenced by closing a supervisory control-loop via the driver. The aim of this paper is to develop a trip management (TM) as a supervisory control for the EV's energy management that provides recommended maximal vehicle speeds and acceleration limitations to the driver under the condition to reach the trip destination with the highest

possible velocity, i.e. yielding the best time/energy consumption trade-off.

Realization of such an algorithm can be thought as driver assistance by suggesting a particular drive-style which the driver needs to be made aware of. A literature review provides a number of approaches to energy management, mainly applied to plug-in, full, and mild hybrids. Most of the reported methods work either to identify an energy management trajectory by an analytical method (e.g. dynamic programming (DP) [2], Pontryagin minimum principal (PMP) [3], [4], or by establishing an energy management heuristic [5], [6], [7]. Rule-based approaches are often successfully employed in industrial automotive applications, but the time-consuming controller design depends only on the vehicle's current state and input variables through some maps. These maps are constructed from engineering expertise or using more formal methods (e.g. fuzzy logic [8], artificial neural networks [9]), which limits the results to a specific vehicle design. Trajectory energy management algorithms require knowledge of future energy demands and use this information to control the vehicle in an optimal sense. Such optimization can be performed offline for drive-cycles a-priori known, but clearly this is not a practical scenario for a trip management. A trade-off between optimality and level of information is needed. Many suggestions can be found to increase the level

of trip information mainly based on global positioning system (GPS), geographic information system (GIS) and historical data. For example, drive pattern recognition with DP solutions has been proposed in [10]. A deep investigation of the potential of an intelligent transportation system (ITS) and the established statistical and heuristic relationships of road events, like road profile, velocity profile, trip distance, and weather conditions to the performance of the energy management can be found in [11] and [12]. Many of the statistical relationships are based on Markov chain models, especially when a number of drive-cycles can be found statistically representative of the vehicle utilization. Then, stochastic dynamic programming (SDP) appears particularly appealing. Recent research results show improvements in energy consumptions due to the ability to optimize the hybrid powertrains for a probabilistic distribution of many drive-cycles rather than one single drive-cycle [13], [14]. However, the SDP approach is well-recognised to require a significant amount of data for validation and large computation time [15]. The latter characteristic makes it difficult to implement this technique in a real-time algorithm. The work presented in this paper extends the results discussed in [16] by an optimization strategy for EVs which uses deterministic routing information and stochastic descriptions of process uncertainties such as stop events as unpredictable disturbances. A real-time implementable DP solution on spatial domain is proposed (originally recommended in [17] and further developed in [18]) using deterministic trip information from GPS and digital maps (e.g. speed limits, curve radii, intersections, road slopes, etc.) combined with stochastic traffic information such as probabilities of stop events generated from historical data. The latter one will be used to improve the predictions of energy usage for disturbances over the whole driving trip. The benefit of the proposed TM is its simplicity, which makes it applicable with nowadays available navigation systems on the market.

DESCRIPTION OF THE PROCESS

Table 1. Parameters of the Electric Vehicle

Vehicle class	subcompact
Weight	1085 kg
A* _{cw}	0.66
Transmission Type	1 fixed gear
Electric Machine Type	PMSM
EM-Power	60 kW
Battery Capacity	77Ah
Nominal Voltage	330V

The considered EV belongs to the subcompact vehicle class and employs a high speed electric machine and high energy battery. The high speed electric machine is a permanent magnet synchronous machine (PMSM) which has the benefits of being light, highly efficient and well controllable. The high voltage battery used is based on

Lithium Ion (Li-Ion) technology and has a capacity of $Q_{bat} = 77 \text{ Ah}$. Some of the vehicle specifications are listed in [Table 1](#).

Models of the Electric Powertrain

The overall powertrain dynamics of an EV are governed by the road loads, the drivetrain inertias and the battery. The total friction force is acting on the EV's powertrain as follows

$$F_{road} = F_{drag} + F_{roll} + m(1 + \lambda)g \sin \chi(t) \quad (1)$$

where the contribution due to drag force F_{drag} and rolling resistance force F_{roll} is best approximated by a polynomial of second degree of the vehicle speed as

$$F_{drag} + F_{roll} = a_2 v^2 + a_1 v + a_0 \quad (2)$$

usually determined during a coast-down experiment on a chassis dynamometer, v , χ , m , λ , g represent the vehicle speed, the road slope, vehicle mass, mass correction, and the acceleration of gravity, respectively. The road loads act on the EV's powertrain through the final drive i_{FD} and a simple one-gear transmission with the fixed gear-ratio i_{01} . The longitudinal vehicle dynamics can then be calculated using the aggregated vehicle inertia J_{veh} as

$$T_{road} = r_{wh} F_{road} \quad (3)$$

$$T_{wh} = J_{veh} \dot{\omega}_{wh} + T_{road} + T_{brk} \quad (4)$$

$$\omega_{wh} = \frac{v}{r_{wh}} \quad (5)$$

where T_{road} is the road load, r_{wh} is the radius of the wheel, T_{wh} is the wheel torque, ω_{wh} is the angular wheel speed and $T_{brk} (> 0)$ is the mechanical brake torque generated by a hydraulic friction brake which cannot be coordinated by the electronic control unit (ECU). A direct proportionality between wheel angular speed and vehicle speed is assumed, thereby neglecting tire slip for simplicity [14]. Through the usage of just one simple gear, the dynamics of the angular speed of the electric drive can easily be expressed as

$$\begin{aligned} \dot{\omega}_{M/G}(t) &= \frac{i_T^2}{J_{veh}} T_{M/G} - \frac{a_2 r_{wh}^2}{i_T} \omega_{M/G}^2 - \dots \\ &\dots - a_1 r_{wh} \omega_{M/G} - a_0 i_T - i_T m(1 + \lambda)g \sin \chi \end{aligned} \quad (6)$$

where $i_T = i_{FD} i_{01}$ is the total transmission gear ratio. The battery can be idealized as an open-circuit voltage (OCV), V_{oc} , in series with some internal resistance, R_{bat} . Both depend on the battery's SoC. The dependency of OCV from SoC can be determined by the Nernst-equation

$$V_{oc}(SoC) = N_c \left(E_{00} + \frac{R \cdot T}{F} \cdot \ln \left(\frac{SoC}{100 - SoC} \right) \right) \quad (7)$$

where N_c , E_{00} , R , F , T are the number of cells, the standard cell potential, the universal gas constant, the Faraday constant, and the cell temperature, respectively. Considering the losses caused by the battery's internal resistance and applying Kirchhoff's law one obtains the battery power P_{bat} related to the current, I_{bat} , through the following power balance equation

$$P_{bat} = V_{oc} I_{bat} - R_{bat} I_{bat}^2 \quad (8)$$

whereas the dependency of R_{bat} from SoC is predefined in maps. Solving Eq. (8) yields the battery current as

$$I_{bat} = \frac{-V_{oc}(SoC) + \sqrt{V_{oc}^2(SoC) - 4R_{bat}(SoC)P_{bat}}}{2R_{bat}(SoC)} \quad (9)$$

The state equation can then be written as

$$\frac{d(SoC)}{dt} = \frac{1}{Q_{bat}} I_{bat}(t) \quad (10)$$

where Q_{bat} is the maximal battery capacity. The charging or discharging efficiency of the battery, η_{bat} , can be evaluated for different stationary operating points and stored into a lookup table (LUT).

Transformation to the Spatial Domain

To reduce the dimensionality for the real-time DP, the state equation (10) of SoC and the corresponding power balance equation (8) must be converted from the time domain into the spatial domain by simply dividing Eq. (10) by the vehicle velocity (>0) which yields

$$\frac{d(SoC)}{dr} = \frac{1}{Q_{bat}v(r)} I_{bat}(r) \quad (11)$$

Relating the power P_{bat} to the requested power at the wheels gives

$$P_{bat}(r) = F_{road} \cdot v(r) \cdot (\eta_{M/G}^+)^{-1} + P_{On} \quad (12)$$

where $\eta_{M/G}^+$ is the motor efficiency of the electric machine only for propulsion, P_{On} is the sum of all electric loads, e.g. electrical steering, electrical air conditioning, etc., and $v(r)$ is the vehicle velocity at the spatial coordinate r .

This procedure drastically reduces the number of grid points as compared to the time domain. For notational clarity, the spatial domain is distinguished from the time domain by

writing r instead of k . Finally, discretizing the angular speed dynamics of the electric machine in the time domain and the SoC dynamics in the spatial domain and combining both with a discretized form of the longitudinal vehicle dynamics results in the deterministic EV plant dynamics in time and spatial domain.

TRIP MODELING

A trip is defined as a driving path from an origin to a destination. Figure 1 shows four exemplary trips nearby the city Wolfsburg and each of them with different distributions of city, country roads and freeway (German Autobahn) parts. The origin is mainly the development center of iav engineering in Gifhorn, while the end location is different. Each trip is stored into a GIS conforming database. Using an electronic horizon provider as interface one can use search algorithms inside the GIS to look for the associated road information for each segment such as segment length, road heights, slopes, curve radii, traffic sign distributions and speed limits. This information has been collected with the Floating-Car method using a car equipped with a GPS device. The traffic signs were entered subsequently.



Figure 1. Route map for the considered trips

Each trip is divided into N number of distance segments based on the change of speed limits and the road slopes. The principal of segmentation is shown in Fig. 2.

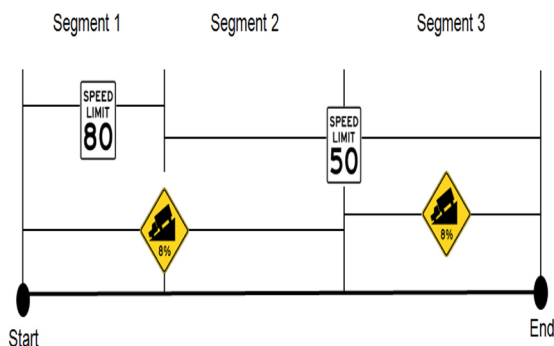


Figure 2. Segmentation based on the changes of speed limit and road slope.

Along the distance, the road slope will be averaged until a change in the sign indicates the beginning of a new segment. If the change in the mean-values of the road slopes from two neighboring segments is smaller than $\pm 1\%$ the segments will be merged together.

The four routes are characterized in Table 2.

Table 2. Characteristics of the selected routes

	Gifhorn -cycle	Wolfenbüttel -cycle	Wolfsburg -cycle	Gifhorn -cycle 2
color	blue	black	green	red
begin	Gifhorn	Wolfen- büttel	Gifhorn	Gifhorn
end	Wolfen- büttel	Gifhorn	Gifhorn	Gifhorn
average speed [m/s]	16.10	15.96	17.04	15.74
distance [km]	40.27	68.77	74.19	67.60
freeway [%]	44.3	54.3	34.9	48.8
country road [%]	35.7	21.3	36.6	32.9
city [%]	20.0	24.4	28.5	18.3
traffic lights	18	49	45	23
yields	4	7	3	10
cross- walks	0	0	4	3
round- abouts	1	4	4	2
railroad crossings	2	2	2	4

The first three trips have been used as learning cycles to reflect valid stop probabilities. The 4th trip has been chosen as a benchmark cycle for the assessment of the trip management algorithm.

Stochastic Events

Stop events which cannot be determined from the GIS database using the electronic horizon provider are classified as stochastic. This classification holds for the following traffic signs: right before left, grant right of way, traffic lights, roundabouts, pedestrian crossings, etc. They are referred to as stochastic stop classes. A number of independent experiments (70 times driving of one of the three learning routes) have shown that there is a correlation between the number of stochastic stop events, the quasi steady velocity, and the daytime. The Figures 3 and 4 show the expected values for some stochastic stop classes depending on the quasi steady velocity and Fig. 5 shows the expected values depending on the daytime. It is immediately obvious that the number of stops increases at the rush hours. It can also be observed from Figs. 3 and 4 that some stochastic stop classes for different learning cycles have approximately the same stop probability which is a justification that the stop probabilities can be marginally adapted.

The probability distribution of each stop class has been estimated by a maximum likelihood estimator which reveals in all cases a normal distribution. An example of the normal distribution is depicted in Fig. 6 for all stop probabilities of occurring traffic lights in all learning cycles.

To avoid multiple counting of the same stop event, due to inharmonic traffic densities, each stop event must be observed with an individual radius around the traffic sign. That means observations of velocities before and after passing the traffic signs. Figure 7 shows an example of a double stop at the same traffic light.

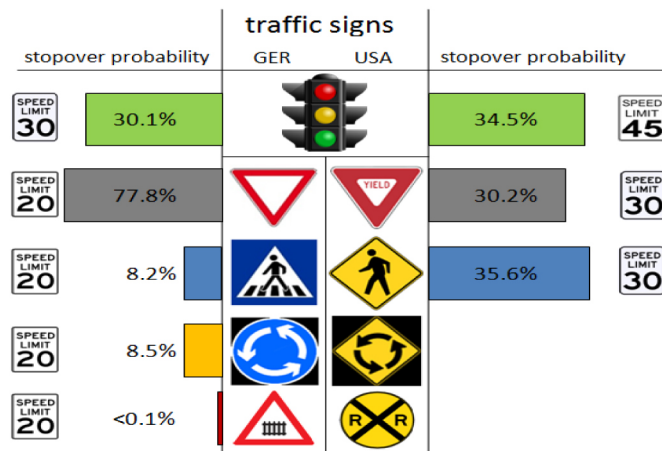


Figure 3. Traffic signs with stop probabilities (Gifhorn-cycle)