EVS30 Symposium
Stuttgart, Germany, October 9 - 11, 2017

Electric Vehicle Energy Efficiency Through Route Analysis and Maximum Speed Control

Victor Ottan Soares de Souza Lima[1], Carolien Stroomer-Kattenbelt[1],Bram Veenhuizen[1], Chris Huijboom[1]

[1] *Hogeschool van Arnhem en Nijmegen Control Systems Research Group, Ruitenberglaan 26, Arnhem, The Netherlands, email: ottanlima@gmail.com*

Summary

Commercial electrical vehicles (EVs) nowadays entered the market as a reliable means of transportation. However, the electric vehicle (EV) range is still a great concern among potential customers. In this paper a solution is proposed, that is a step toward guaranteeing arrival at the desired destination. An offline model is proposed that predicts the vehicle consumption on a specific route and an energy management strategy to reduce the battery consumption by limiting its maximum speed. The system results are presented in the form of predicted state of charge and the system with an energy management system state of charge.

Keywords: *EV (electric vehicle), State of Charge, Energy Consumption.*

1 Introduction

"The first demonstration electric vehicles were made in the 1830s and commercial electric vehicles were available by the end of the 19th century. The electric vehicle has now entered its third century as a commercially available product and as such it has been very successful, outlasting many other technical ideas that have come and gone.". Today's interest about the environment are even a greater incentive to develop new technologies in battery and fuel cells in favor of electric vehicles [1].

The battery size of an electric vehicle (EV) today is still a limitation to its range. For electric vehicle users there is always a concern that the battery will run empty before the destination is reached which is one reason that makes consumers still choose internal combustion cars. [1]

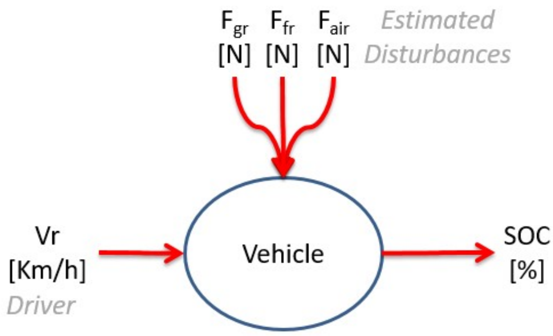
To increase the distance traveled by an electric vehicle it is possible to enlarge the battery capacity. However, a large battery normally is heavier and more expensive. As a solution to the problem of range extension it is possible to see some applications suggested in [2-5] that focus on dynamic programming to find the optimal fuel or battery consumption route applying into hybrid and full electric vehicles. An extended range vehicle controller approach based on the route load can be seen in [6].

However, to obtain the guarantee the arrival and therefore, overcome the uncertainty of arriving at the destination, an optimal energy consumption approach is not necessary. Thus, in [7-8] it is approached a system to evaluate the energy consumption in a route and to manipulate the vehicle inputs to reduce the battery discharge rate without focusing in optimizing it. The approach is to evaluate the battery state of charge, showing if it is possible to reach the desired destination, based on the expected vehicle speed, road height, length and control the top speed, auxiliaries and vehicle acceleration with an offline model. Then, to guarantee the vehicle arrival at the destination with the predicted SOC independent of the road parameters deviations by manipulating the vehicle inputs with an online system.

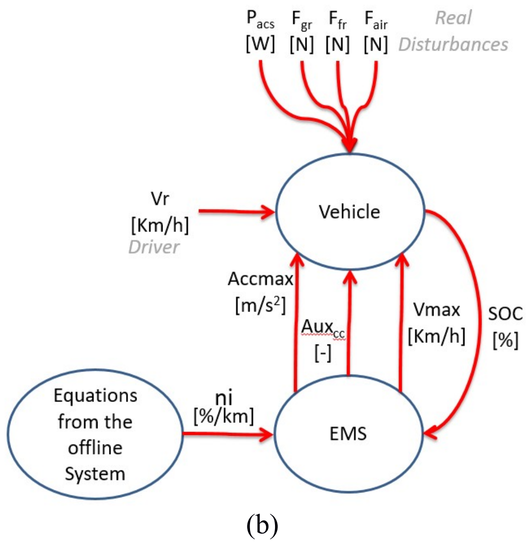
To build such a system, it is necessary to have a vehicle energy model that relates the power consumed by the motor with the torque (that eventually translates into speed), road load and air drag force, which is built offline with collected parameters from the route. [9] describes a model design of the car focusing more on the electric motor modelling. On the other hand, by checking [10, 6-8] it was possible to see an energy vehicle model with more focus on the driver behavior, which was a simpler approach for the project and thus the chosen one.
Matlab and Simulink were used to simulate the offline and online system. The vehicle parameters were based on a real light vehicle. The difference between the vehicle model applied in the online and offline system are some parameter changes into the simulation that are explained further.
The structure of the paper consists in section 2 the vehicle model is presented, in section 3 how to guarantee arrival is presented, in section 4 the energy management system design is shown and at least the section 5 the results are discussed.

2 Electric Vehicle Model

The energy consumed by an electric vehicle is highly dependent on the load on its motor axis (slopes, total vehicle weight, how aggressively the driver is riding). Thus, the battery consumption of the vehicle can be determined by equations that relate the speed of the motor, air friction, road friction and slope that the vehicle is subjected to. By knowing that, it is possible to design a model, predict the consumption of the vehicle on a determined route and thereby calculate if the final destination can be reached. Later, the model results are applied into an online system that consists, in this paper, of the same model used for the offline model with some different parameters to simulate a real world situation.
In figure 1 it is possible to see a diagram which summarizes the inputs, outputs and disturbances for the offline vehicle model and online system.



(a)



(b)

Figure 1: Diagram for inputs, outputs and disturbances for the vehicle model (a) and online system (b)

By V_r being the vehicle speed as an input (desired speed), F_{air} is the air drag force, F_{fr} is the counter force due to road friction and F_{gr} is the counter force due to road grade and SOC is the battery state of charge. The information given by the driver input (V_r) is the driving cycle and it has the information of acceleration, stop events and maximum speed. For using this input, it is possible to have a relationship between the state of charge and driving behaviour.
In the online system it is possible to see the P_{acs} as the power from accessories, n_i as the predicted SOC consumption per kilometre uploaded into the energy management system and the manipulated inputs maximum acceleration (Acc_{max}), Aux_{cc} as a factor to reduce the auxiliaries total power and top speed (V_{max}).
In figure 2 it is shown the data flow diagram for the model with more details.

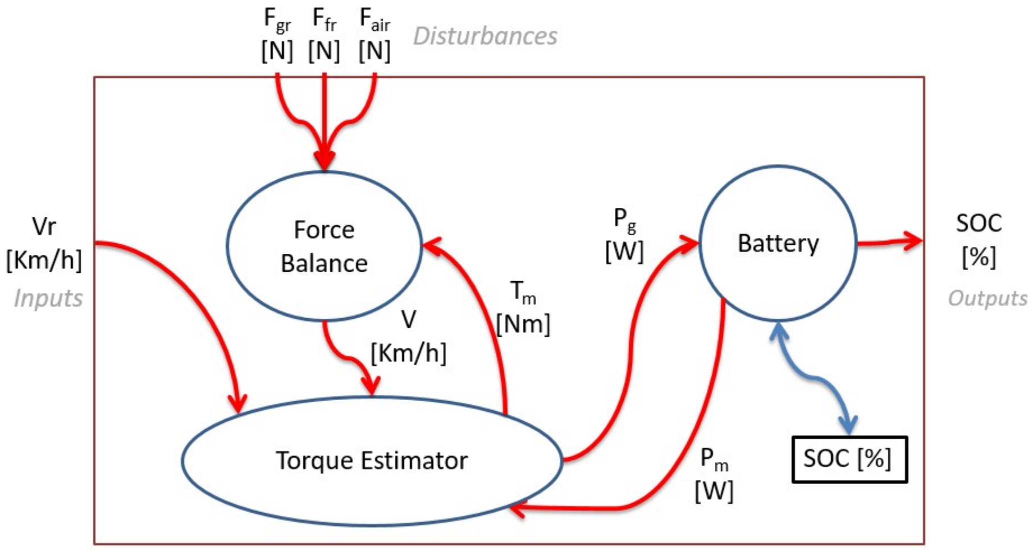


Figure 2: Dataflow diagram for the vehicle model

The torque estimator evaluates the torque (Tm) based on the interaction between disturbances and the input speed given by the driver (Vr). The speed output on the force balance subsystem (V) is feedback into the estimator to guarantee that it calculates the correct torque. When accelerating and breaking the vehicle will demand power from/to the Battery (Pm and Pg) and then the resultant consumption integrated in time will reduce or increase the battery state of charge.
To model a vehicle energy performance, it is necessary first to produce an equation for the tractive effort (force balance equation). This force is the one which propels the vehicle forward [1]. Therefore, to model the tractive force needed to achieve a certain speed, the equation used was:

$$M\dot{v} = F_{tc} - F_{fr} - F_{gr} - F_{air} \tag{1}$$

With M being the mass of the total vehicle mass plus the moment of inertia from the motor to the wheel, F_{tc} is the tractive force from the motor, F_{fr} is the road friction, F_{gr} is the grade force and F_{air} is the air drag force. According to [1], the final equation is:

$$\dot{v} = \frac{\frac{G}{r}T - u_{rr}mg - mg\sin\theta - \frac{1}{2}\rho A C_d v^2}{m + \frac{J_{eq}}{\mu_g r^2}} \tag{2}$$

Due to the fact that the input of the model is the driving cycle, the torque is evaluated by the estimator shown in figure 2 and it was designed based on the vehicle full throttle acceleration value.
After modelling the vehicle dynamics is possible to know how much torque is required from the motor for the vehicle to reach a desired speed. By knowing the vehicle torque and speed is possible to derive the electric power the motor demands by the following equation:

To evaluate the SOC the following equation is used, according to [1, 6]:

$$SOC = SOC_{ini} - SOC_{cns} + SOC_{chrg} \tag{3}$$

$$SOC = SOC_{ini} - \frac{\int P_m dt}{Q\mu_b} + \frac{\mu_b \int P_g dt}{Q} \tag{4}$$

By SOC_{ini} being the initial state of charge, P_m is the power demanded from the motor, P_g the power generated by regeneration from breaking, Q the total battery capacity in Ws and μ_b the battery efficiency. To calculate the power generated and consumed by the motor, an efficiency map was used obtained from the supplier.

2.1 Driving Cycle Design and Validation

Two important inputs for the vehicle energy modelling are the driving cycle and the route. The driving cycle is the speed profile which describes the driver behaviour and stop and go events on the track and it is used as a reference for the torque estimator.

Before evaluating the influence of each input in the output values with the sensitivity analysis it is necessary to build the driving cycle. The real driving cycle was approximated as a series of trapezoidal shaped speed profiles that mimics the acceleration, cruise and breaking behaviours of a car in a certain length [7]. The final goal is to build the driving cycle based on the vehicle acceleration, cruising speed and stop and go events across the route and then validate it with data from the vehicle in an urban environment. Thus, it was built in three steps:

- The vehicle accelerates from zero to maximum speed.
- Then the vehicle maintains the maximum speed for some length.
- And then decelerate till the vehicle stops.

The use of this particular method is motivated by that the difference between driving cycles are easy to obtain just by changing the maximum speed and length between start and stops which, according to [7], ease the sensitivity analysis.

The driving cycle is length dependent because in a real urban situation the number of stop and go events are already fixed in a route, i.e., traffic lights and crossroads. Certainly these are not mandatory stops but it can be approximated as such.

The top speed chosen for the driving profile is 50 km/h judging that this is the average maximum speed a car will travel inside the urban limits in Europe. The length between vehicle start and stops for each cycle was based on an average stop and go events inside urban perimeter (from 150m to 550m). The motivation for the breaking and acceleration lengths choice are that they represent a real urban situation, which was based on a dataset given to validate the driving cycle, as going to be described later.

For each designed driving cycle, the vehicle accelerates and breaks with a fixed acceleration of 1.756 m/s^2 and just the cruise length is modified according to the total cycle distance.

After building the speed profile with different lengths a validation step is needed to be sure which profile fits better a real driving scenario.

To validate the driving cycle, it is necessary to have real world consumption and speed measurements and compare them with the presented model. This is important to have a baseline for the model input. However, there was no vehicle prototype provided to make such tests. Therefore, the Hogeschool van Arnhem en Nijmegen automotive department provided raw data from three Hyundai ix-35 that are used to travel inside Arnhem, Netherlands and two other cities to do the validation step.

With all the data given, the first step is to input all the model parameters to match ix-35, which is a different vehicle. The second step is to filter from the given raw data inside urban range trips. This was done by

checking the driving cycle behaviour, top speed and trip length. With all properly filtered data, the next step was to build each route for each trip in the simulation file to make sure that the road is similar to the real one.
By doing all the former steps, simulation tests are made with four different chosen routes obtained from the dataset. Each driving cycle built (from 150m to 550m stop event length) was tested in each road profile by limiting the speed from 10 km/h to 50 km/h, the average speed and the battery discharge rate on each test were evaluated and compared with the real vehicle average consumption and speed. The results of these tests can be seen in figure 3. It is important to mention that the battery capacity is 8.6 kWh.

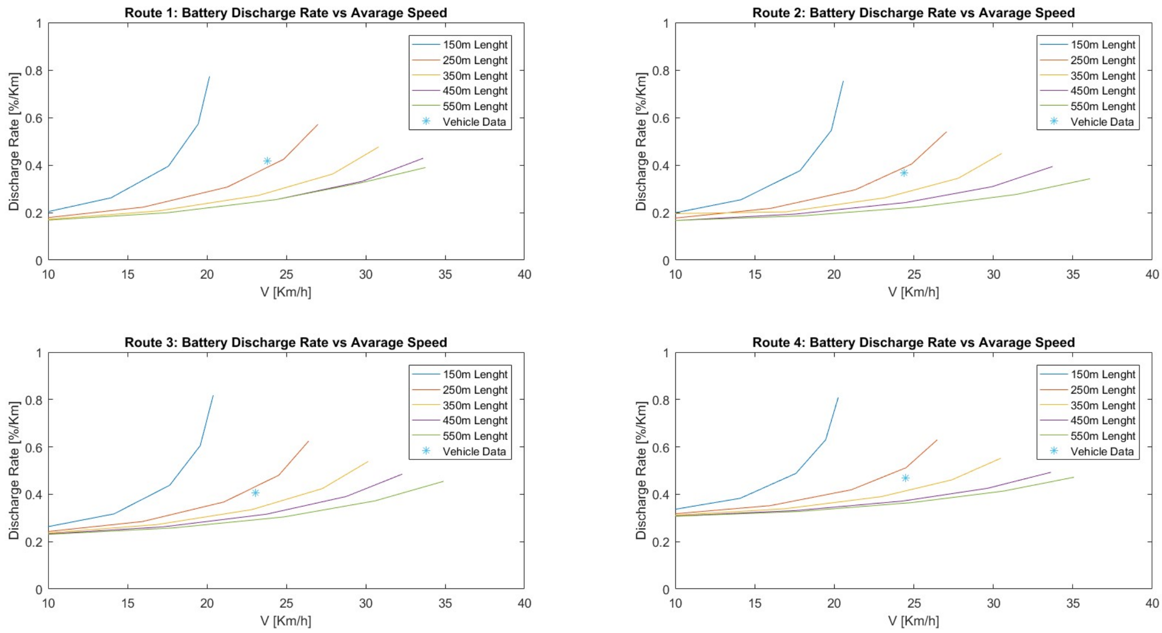


Figure 3: Discharge rate of each driving cycle compare with the real vehicle data based on a 8.6 KWh battery

By checking the plots, the more stop events you have the more related is your consumption is sensitive to average speed. The deviation seen from the number of stop events in a determined route can promote a significant change on the vehicle consumption, which can depend on the average speed and the length between each stop.
Another remark is that the real car battery discharge rate by its average speed is surrounding 250m driving cycle length, which are the stars on the plots. That means that the real vehicle had a similar consumption as the model when the 250m driving cycle. Then, this is the most accurate speed profile compared to a real world data and therefore the one that will be used for the whole sensitivity analysis and controller application test.

3 Guarantee Arrival

To predict more accurately the state of charge and make the EMS possible to guarantee the arrival to the final destination, it was necessary to first make a sensitivity analysis to state which inputs are more influential to the vehicle consumption . This study is important to determine which model inputs should be neglected or used into the energy management system and later to be used into design a probability of arrival scenario for the vehicle to be possible to a decision be made about driving or stop to recharge the vehicle.

3.1 Sensitivity Analysis

For this analysis, six tests were done using the offline system built in Matlab/Simulink model, changing one input at each time. The inputs changed were: top speed, acceleration, the coefficient of rolling resistance, wind speed, stop and go events and road gradient. Other parameters were get form the suppliers like the vehicle accessories and the battery capacity versus temperature (figure 4) [11].
The result for the sensitivity analysis can be seen in table 1.

Table 1: Overall result for the sensitivity analysis

Analysed Input	Change in the Input	Change in the Output
Top Speed	5 km/h	Up to 0.05 %/km
Acceleration	Reducing the acceleration by 0.75 m/s^2	Up to 0.0448%/km less consumption
Auxiliaries	-	5 % more energy
Coefficient of Rolling Resistance	0.05	Up to 0.0338 %/km
Wind Speed	5 Km/h headwind	Up to 0.07 %/km
Gradient	1º	Up to 0.3 %/km

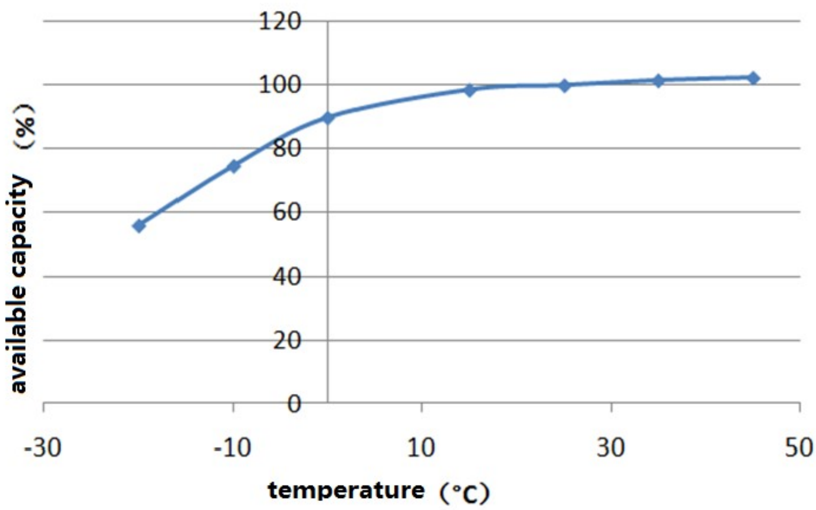


Figure 4: Total lithium capacity versus temperature [11]

The results from the sensitivity analysis show that some inputs are more influential than others. The top speed analysis shows that the changing just 5 km/h of speed can guarantee more than 0.5% of consumption reduction for 10 km length. This speed value is not much and it is most likely to the vehicle velocity fluctuates around this value.
The coefficient of rolling resistance simulation showed to have not so much influence on the discharge rate. A change from the minimum to the maximum value possible in hard soil (0.01 to 0.015) according to [12]- just represents a 0.034 %/km change on the consumption, which is sufficiently negligible is due to the fact that it is a value that will rarely change much because of its high dependence with the type of road and tire

pressure, which do not likely to variate so much. Thus, the variations in the rolling coefficient does not produce much uncertainty in the final SOC value.
The wind speed is expected to have a substantial fluctuation on the output due to its deviation. The relative wind speed variation can be very significant because it is influenced by effective vehicle area that is encountered by the wind and direction where the wind is blowing .Thus, the wind speed was added to the controller as a measurable (from the forecast) disturbance to predict the state of charge on the route and the use of this will be described in the EMS section.
With the gradient sensitivity analysis, it was noticed that it is a very influential input. One degree of change on the road slope, which is translated as about 17 meters of altitude by driving in 1 km route, means a change in up to 50% on the discharge rate. Therefore, the gradient is a route parameter that can be easily obtained by Google cartography data and it is very influential to the battery discharge dynamics it was considered when the controller was built and it is the baseline to how the route was divided in different sections.
The acceleration showed to be not very influential to the discharge rate due to the fact that reducing the acceleration by a factor of 2, amplitude the consumption just decreases 0.08 %/km which is less than a 10% reduction. The combination that is due to the driving cycle used of 250 meters, which reduces the transient influence in relation of the cruise top speed. Thus, due to limiting the maximum vehicle acceleration change the vehicle dynamics, which can influence on the final driver reaction time to avoid an accident and that the acceleration variation does not add, proportionally with the top speed, that much uncertainty into the state of charge evaluation, the EMS just manipulates the top speed.
The temperature can influence the battery up to 20% by considering Netherlands temperature. But on average it will influence up to 10% on the winter. The auxiliaries can influence up to 5% on the total consumed energy, which is not much compared to the other parameters but it will influence the final destination SOC.

3.2 Decision Making

By checking the final SOC level when the offline system runs and the deviations generated by the parameter uncertainty it is possible to know whether or not the final destination is reachable and make the decision to drive the vehicle or to go to a charging spot. According to what is seen in last sub-section a deviation in acceleration and coefficient of rolling resistance values can be neglected due to the low influence in the discharge rate in relation with the input value. However, the auxiliaries, wind speed, gradient, ambient temperature and speed deviation can cause a certain degree of uncertainty on the final state of charge.
Therefore, in this section a study on the probability of the most influential parameters deviate from their expected value and how that would influence on the battery discharge rate and consequently on the final SOC value is presented with a possible practical scenario. These deviations can be caused by measurement errors from the sensors in the car or the data obtained from the internet (GPS error or wind speed variations). The parameters were assumed to have a known standard deviation and to cause a corresponding battery discharge rate deviation.
In table 2 the values for the standard deviation for the parameters and output can be checked. Due to the fact that there is no data on the sensors and internet parameters error, these deviations were all assumed. The temperature deviation will be added further on the analysis to check what should be the deviation on the total battery capacity.

Table 2: Standard deviations for the most influential parameters

Input	**Standard Input Deviation**	**Standard Output Deviation**
Top Speed	± 1 km/h	± 0.0094 %/km
Wind Speed	± 5 km/h	± 0.0621 %/km
Gradient	± 0.5 º	± 0.0622 %/km

By knowing that the discharge rate from the inputs are an addition to the output, which means that the bigger the wind speed the steeper is the battery discharge rate curve, the standard output deviation is:

$$\sigma_t = \sqrt{\sigma_s^2 + \sigma_w^2 + \sigma_g^2} \tag{5}$$

Substituting all the three standard deviations from the inputs into the equation, it is obtained the total standard deviation, which is ± 0.0884 %/km. This result makes very clear that the gradient and wind speed deviations dictate the final one, which means that the more precise the road grade and wind speed information is obtained the more accurate the system can be. The probability distribution function (PDF) for the parameters deviation is shown in figure 5.

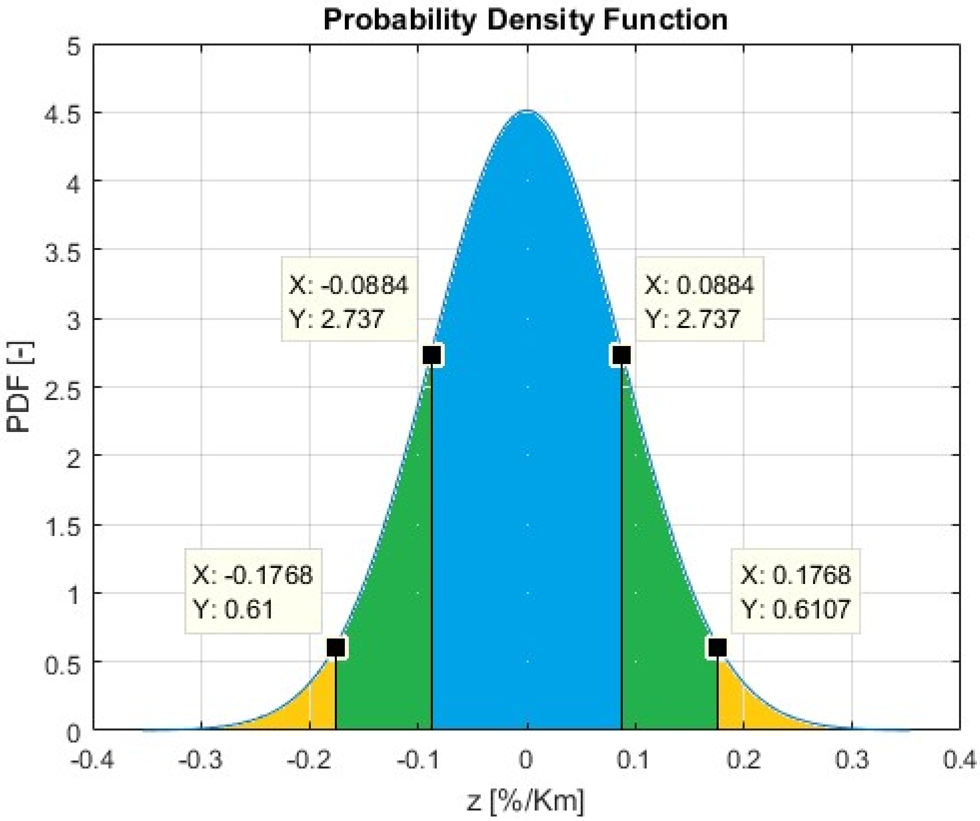


Figure 5: PDF for the deviation of wind speed, top speed and road grade

The PDF plot shows that for the probability for the final deviation be inside the ± 0.0884 %/km range (blue area), which is the total standard deviation, is approximately 68.26%. However, the probability to be in the green and yellow area is 31.74%, which means that the values being deviating around the total standard deviation range is more likely to happen.

Considering the standard deviation for the temperature from the vehicle temperature sensor being 1 ºC, which reflects a standard deviation in 0.4% of battery total capacity, it is more probable that there will be a deviation on the total battery capacity inside this range.

To take some conclusions from these deviations analysis, it is necessary to build a practical scenario to show what are the possible consequences of parameters fluctuations. In this analysis, the worst case values possible will be assumed in the yellow area where they are deviating from double the standard deviation (2.28 %) probability to have a value inside this area and therefore the study will be directed to this area.

3.3 Practical Scenario

For the practical scenario the route with the parameters seen in table 3 was chosen:

Table 1: Parameters for the road

Parameters	Values
Top Speed	50 km/h
Wind Speed	15 km/h
Gradient	0 º
Temperature	8 ºC
Route Length	80 km
Initial SOC	100 %

By applying the parameters found in table 3 into the offline system, the final battery SOC is 24.45%. However, due to the temperature effect, the total battery capacity is reduced to 95% (check figure 4) which reduces the final state of charge to just 19.45%. If the standard deviation for the temperature is considered, 2.28% of probability to the temperature measurements deviating beyond 2ºC that reflects on real final value be at the 18.65%, which makes the temperature deviation not be a great source of uncertainty on the offline system. For a final analysis, the vehicle auxiliaries are added into the account and it is more 5% into the total energy vehicle consumption and basically reducing the total final state of charge to 13.65%, if the air comfort system is on the whole trip.

After evaluating the direct deviation on the final state of charge it is necessary to check the deviation on the consumption caused by the parameter fluctuation. The deviation on the road parameters has a 2.28% probability to promote a deviation of minus 14.144% on the final SOC (0.1768%/km for 80 km). This variation can increase the uncertainty on the offline system accuracy. On the other hand, when the online system is applied it can easily compensate this deviation due to the fact that in the max speed controller can reduce up to 14.792% (0.1849%/km for 80 km) and therefore guarantee the arrival for the driver.

By analysing all the odds described on this section the probability of the online controller compensating the possible deviation is bigger than not due to the fact that the energy management system can compensate up to 0.1849%/km and the double standard deviations are around 0.1768%/km. Another factor is that the temperature and auxiliaries influence on the SOC is not enough, in this case, to cause an impact on the final state of charge.

In this case scenario it is valid to say that, by not taking into account the state of charge measurement error, the difference between the negative influence on the consumption by the speed limitation and the positive influence due to the road parameter deviation must not be bigger than 0.1706%/km. This means that the total deviation should be, at least 0.355%/km, which reflects a probability smaller than 0.02%. Therefore, the probability of not arriving in this assumed case scenario is smaller than 0.02% and by that it is possible to make the decision to start the trip without the need to stop to recharge. It is important to mention that the decision making was not implemented into the offline nor the online system in this study.

After making the decision to drive, the online system will be the one which control the top vehicle speed to maintain the consumption as expected with the offline system. This will be described on the following section.

4 Energy Management System

After having the certainty that it is possible to do the trip, the energy management system will maintain the battery state of charge equal to the one predicted by manipulating the vehicle top speed. In figure 6 it is shown the online system which is composed by the EMS.

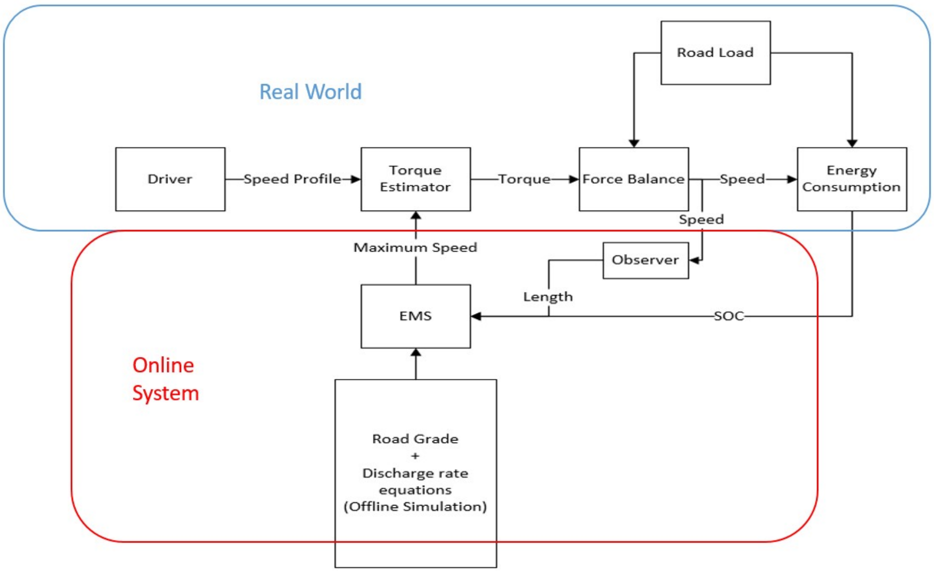


Figure 6: Online system diagram

Basically, the EMS receives the information of predicted consumption and road grade from the offline model. After obtaining it, the system collects the current battery SOC value during the trip and compares it to the predicted one. It is important to know the grade and obtain the current position to know at which route section the vehicle is. Depending on the current consumption compared with the offline one, the top speed is reduced or increased. The range for the controller was chosen from 30 to 50 km/h due to the vehicle is limited to an urban environment.
In the next section the results are going to be presented

5 Results

To check the system controllability, it is necessary to know how much the top speed influences the battery discharge rate. It was built a route and it was divided by five sections with the slope angle criteria, due to the high road grade influence). In table 5 it is possible to check the range of discharge rate (n_i) in %/km for the maximum and minimum speed for each section of the simulated road. The values are based on an 8.6 KWh battery.

Table 5: Battery discharge rate range for each road section

Section	Grade [rad]	Wind Speed [km/h]	Consumption for 30 km/h [%/km]	Consumption for 50 km/h [%/km]	Controllability Range [%/km]
Section 1	0	15	0.7986	1.0174	0.2188
Section 2	0.02	10	0.88	1.227	0.347
Section 3	0.01	0	0.8046	0.9844	0.1798
Section 4	-0.03	0	0.1124	0.4896	0.3777
Section 5	0	-10	0.685	0.8702	0.1852

It is possible to see in table 5 that the average discharge range is around 0.26 %/km which is the controllability range and therefore the maximum percentage per kilometre that can be reduced per section. To test the EMS implemented into the online system, it was applied an added noise to the wind and grade values to simulate a more realistic environment where some estimated does not match with real ones. In figure 7 it is possible to see the online system output for all the disturbances deviations applied at the same simulation.

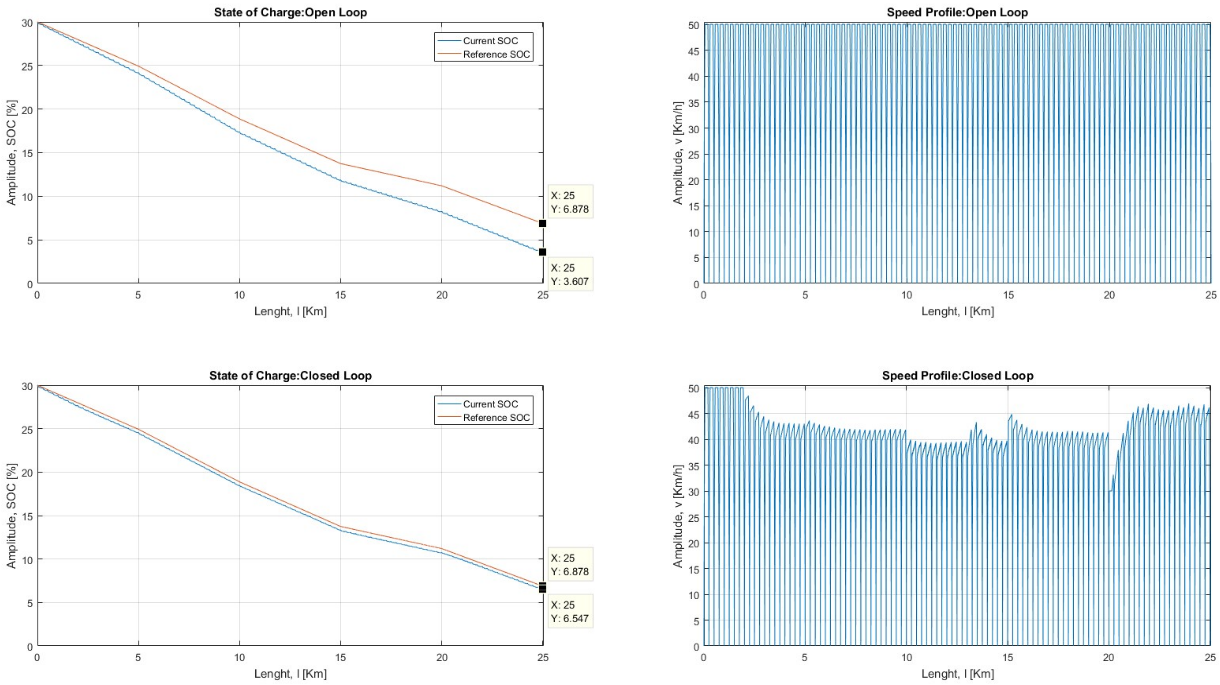


Figure 7: SOC and Speed profile with deviations in the disturbances

Even though a dynamic disturbance of 0.5º on the road grade and 5 km/h on the wind speed is applied to the model, the controller is capable of tracking the reference with a final value error of 0.331%. It is possible to see that there is a top speed reduction to achieve this tracking.

6 Conclusions

In this paper it was proposed a way to model a full electric vehicle with the goal to predict the battery state of charge by the end of a desired route. The results obtained from the simulations were as expected as the battery state of charge was predicted by the offline model.

With the energy management system, it is possible to determine with less than 1% error if the vehicle is going to arrive its destination with sufficient battery state of charge, which is an excellent final result. Nevertheless, there is still an issue with the model design that should be taken into account for this current application. The current designed EMS is highly dependent on the driving cycle which is basically determined by the driver, the route stop events and length between them. The driving cycle used was roughly validated with data from a car which was driven by a different number of people. In addition, the wind speed is unknown for the trips made. Therefore, it is necessary to think in a future application how to make a new driving cycle validation step to get a more accurate driving cycle for the desired light vehicle.

For a future project this algorithm should be applied into the vehicle to see its performance in a real world scenario and add the decision making algorithm to make the system take from the driver the choice between to drive and to recharge.

References

[1] L. James e L. John, *Electric Vehicle Technology Explained,* ISBN: 978-1-119-94273-3, Chichester, England: Wiley, 2003.

[2] Xiaohong Jiao and Tielong Shen, *SDP Policy Iteration-Based Energy Management Strategy Using Traffic Information for Commuter Hybrid Electric Vehicles, Energies — Open Access Energy Research, Engineering and Policy Journal*, Vol 7, ISSN 1996-1073, pp. 4648 – 4675, 2014.

[3] Zhonghao Sun, Xingshe Zhou, *To save money or to save time: Intelligent routing design for plug-in hybrid electric vehicle*, *Transportation Research Part D: Transport and Environment,* Vol 43, pp. 238–250, 2016.

[4] Chensheng Liu, Jing Wu, Chengnian Long, *Joint Charging and Routing Optimization for Electric Vehicle Navigation Systems*, *The International Federation of Automatic Control,* Cape Town, South Africa, 2014.

[5] Tomohisa Hayakawa, Kyohei Ishikawa, Jun-ichi Imura, Hideaki Tanaka, Masumi Toyoshima, Akihito Iwai, Chengnian Long, *Incentive Based Multi-Objective Optimization in Electric Vehicle Navigation including Battery Charging*, *The International Federation of Automatic Control,* Cape Town, South Africa, 2014.

[6] S. M. PI, Y.S BAK, Y. K. YOU, D. H. PARK and H. S. KIM, *Development of Route Information Based Driving Control Algorithm for a Range-Extended Electric Vehicle, International Journal of Automotive Technology*, Vol 17, ISSN 1976–3832, pp. 1101-1111, 2016.

[7] A. Dardanelli, M. Tanelli and S. M. Savaresi., *An Active Energy Management System for Light Two-wheeled Electric Vehicles,* at *7th IFAC Symposium on Advances in Automotive Control*, Tokyo, Japan, 2013.

[8] A. Dardanelli, M. Tanelli, S. M. Savaresi, and M. Santucci, *Active energy management of electric vehicles with cartographic data,* at *2012 IEEE International Electrical Vehicle Conference (IEVC)*, 2012.

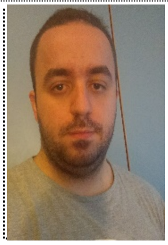
[9] Qi Huang, Yong Chen and Jian Li (2010), *Control of Electric Vehicle, Urban Transport and Hybrid Vehicles*, Seref Soylu (Ed.), ISBN: 978-953-307-100-8, 2010.

[10] S.C. Yang, M. Li, T.Q. Tang , Y. Lin, *An electric vehicle's battery life model under car-following model*, Journal of the International Measurement Confederation, Vol 46, pp. 4226-4231, 2013.

[11] Iian Tech, http://iian.kr/wordpress/?page_id=9531, accessed on 2017-03-21

[12] Engineering tool box, http://www.engineeringtoolbox.com/rolling-friction-resistance-d_1303.html, accessed on 2016-11-07.

Authors



Victor Ottan Soares de Souza Lima was born in Feira de Santana, Brazil in 1988. He received the bachelor degree in electronic engineering in early 2012. In 2015 he joined Hogeschool van Arnhem en Nijmegen (HAN) Master Control Systems program. His main interests in research are modelling and control.

Carolien Stroomer-Kattenbelt is a senior researcher control systems engineering Hogeschool van Arnhem en Nijmegen (HAN). She took her degree in Chemical Engineering with honours from the University of Twenty and received her doctorate in 2008 *Modeling and optimization of slopping prevention and batch time reduction in basic oxygen steel making*

Bram Veenhuizen received his master degree and PhD degree on from the University of Amsterdam in 1984 and 1988 respectively. He joined SKF focussing on electromagnetic and X-ray techniques to characterize materials and material fatigue. In 1995 he joined van Doornes Transmisie, where he was responsible for the realization of some advanced drive train projects. In 2002 he was appointed assistant professor at the Eindhoven University of Technology. Since 2005 he is professor in vehicle mechatronics at the HAN University of Applied Sciences.

Chris Huijboom is a research engineer at Hogeschool van Arnhem en Nijmegen (HAN). He took his bachelor degree at HAN in automotive engineer in 2002 and his master degree in automotive systems in 2015.