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Battery Health Estimation in a Vehicle-to-Grid Scenario

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Executive Summary

Our contemporary society needs to fully decarbonize in order to tackle the climate crisis we are facing. Accordingly, we are in the need of using renewables energies. Unfortunately, renewable energy is intermittent, so an unbalance between demand and supply exists. The issue with e-mobility is the availability of electricity and the grid integration of the charging infrastructure. The onboard energy storage unit of the electric vehicle can act as energy buffer for the electricity grid when bidirectional chargers are deployed, and grid services are offered. Accordingly, the battery is a key element in this scenario. In this paper the basis of a methodology is presented in order to estimate the battery State of Health for a longer and safer use of the battery.

Keywords: Battery ageing, State-of-Health, Vehicle-to-Grid, Machine Learning

1 Introduction

Our contemporary society needs to fully decarbonize in order to tackle the climate crisis we are facing. A twofold transition is approaching, the decarbonization and decentralization of the electricity sector and the electrification of the transport sector. Both transitions come with their own barriers. The aim of this paper is to align both into a mutual reinforcing collaboration. One of the main hurdles of renewable energy is its intermittent nature, creating an unbalance between demand and supply. The issue with e-mobility is the availability of electricity and the grid integration of the charging infrastructure. The onboard energy storage unit of the electric vehicle can act as energy buffer for the electricity grid when bidirectional chargers are deployed, and services are offered (figure 1). In this paper an algorithm is developed that will be able to estimate the State of Heath of the battery and to detect the critical degradation mechanisms (1).

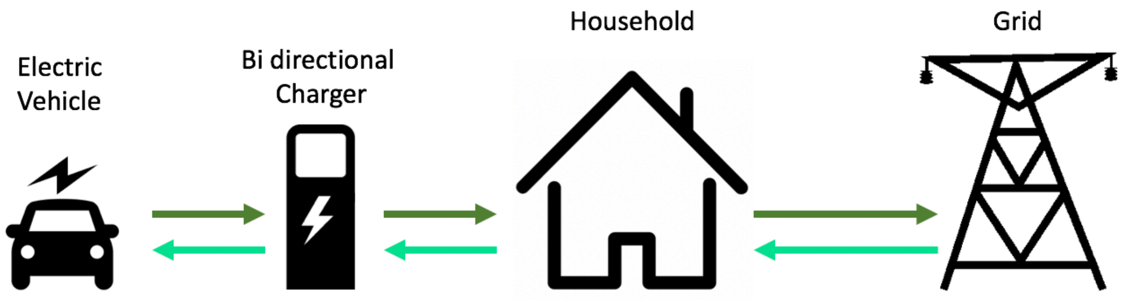

Figure 1: Visual for Vehicle to Grid scenario.

2 Battery Health

Inside a Vehicle to Grid activity the used battery status is key for an optimal usage of the vehicle battery as mean of transport as well as the storage usage. So as to check closely the status of the battery, the estimatin of the State-of-Health (SoH) is needed. The SoH is the ability of a battery to store energy relative to its initial or ideal conditions. It is essential to estimate the SoH in order to ensure a safe and correct usage of the battery. The SoH is presented in percentage, showing that 100% means that the battery is new. Ageing of a battery comes from multiple causes, but it's reflected by two phenomena; capacity and power fade. Capacity decrease is measured by capacity loss, limiting the End of Life (EoL) at 80%. On the contrary, power fade is delimited by the increase of the battery, showing that 200% is the EoL. When arriving to these SoH criteria, the battery is considered not usable and should be replaced (2) (3) (4) (5).

Due to all causes that originate ageing in a battery, the determination of SoH is not a based on a direct measurement. Classical methods require to study interactions on the positive or the negative electrodes. Unfortunately, most of the times these processes require the destruction of the cell, disabling any further use of the cell. Determination of SoH in a less aggressive way can be obtained by two different approaches: adaptive models and experimental techniques. Adaptive models are useful when system-specific information is not available. The strength of this approach is diagnosis. The main problem is that they need training data to determine the current capacity. Classical experimental techniques take into account the physical processes and failure mechanisms that occur in systems, enabling prognosis of capacity. A limitation of these approaches is that they cannot detect intermittent failures (6).

Accordingly, for a Vehicle-to-Grid application it is necessary to develop a new methodology in order to determine the SoH of the batteries which are used in an electric vehicle, in a simple, rapid and non-aggressive way. In order to accomplish these requirements, the Incremental Capacity curves are going to be used. These techniques have emerged recently and have been used by many researchers in order to reveal battery degradation mechanisms occurring in a battery cell. Additionally, with these techniques, the degradation mechanisms occurring in the cell can also be detected. Figure 2 shows the evolution of the IC curves with aging for the four tested cells (7).

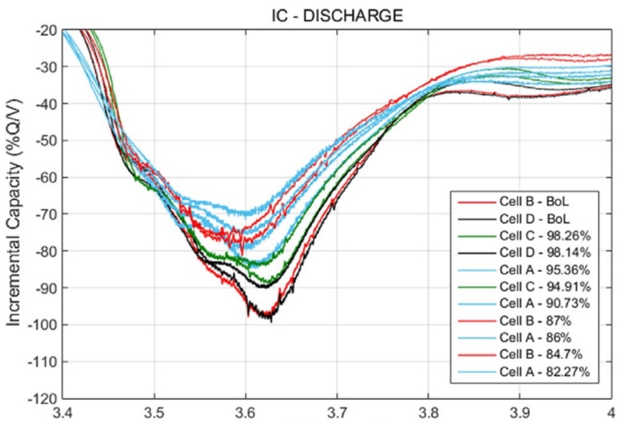

Figure 2: Evolution of Incremental Capacity curves in terms of ageing (7).

3 Methodology

In order to estimate the SoH of the battery in of an electric vehicle, the next methodology has been defined. The method consists on 3 main phases: a) SoH estimation based on the capacity fade, b) SoH estimation based on the internal resistance increase and c) Degradation mechanisms detection.

- SoH estimation based on the capacity fade:

For the capacity fade estimation, a capacity test needs to be performed. This test consists on charge and discharge cycles (at current-constant voltage, in Constant Current – Constant Voltage (CC-CV), and Constant Current (CC) modes, respectively) at nominal conditions specified by cell manufacturer (1C-rate current and 25ºC temperature). Three full charge-discharge cycles are performed in order to assess both reversible and irreversible capacity losses and check the repeatability of the results. The SoH is calculated from the capacity test according to equation (1) were Q is the capacity in Ah (1).

$$SoH_E = \frac{Q_{current}\,(Ah)}{Q_{fresh}\,(Ah)}\ x\ 100\% \qquad (1)$$

- SoH estimation based on the internal resistance increase:

For the resistance estimation, a Hybrid Pulse Power Characterisation (HPPC) test is performed. The HPPC test follows the IEC62660-1 standard (8). This test profile contains both discharge and charge pulses. In this measurement technique, current pulses (ΔI) with various amplitudes (0.5 It, 1 It, 2 It and 2.5 It) are applied to the battery during charging and discharging at different SoC levels (100% to 0% SoC with 5% steps). During the HPPC test, the applied charge/discharge current pulse (ΔI) result in a voltage response (ΔV). The battery internal resistance can be obtained with the following equation (2).

$$R_{inter} = \frac{\Delta V}{\Delta I} \qquad (2)$$

After obtaining the results from the HPPC test, the SoH in terms of power fade is calculated following formula (3).

$$SoH_P = \frac{R_{current}\,(\Omega)}{R_{fresh}\,(\Omega)}\ x\ 100\% \qquad (3)$$

- Degradation mechanism detection:

The detection of the degradation mechanisms is key in order to prevent and predict a possible failure happening in the battery. Accordingly, the incremental capacity curves are going to be tested in this methodology. Incremental capacity has already been used for aging and degradation mechanism detection in lithium ion cells. Hence, different battery technologies have been studied by the application of the IC curves: LFP cells (9), LTO batteries (10), LCO (11) and NMC (12) (13) (14). SoH estimation has also been studied by applying this technique in different battery technologies, like in NMC cells (7),LFP (15) and also composites NMC+LMO (16) cells. The next formula can be used for obtaining of the incremental capacity curves (4) (7).

$$\left(\frac{dQ}{dV}\right)_{cell} = \frac{1}{(\frac{dV}{dQ})_{cathode} - (\frac{dV}{dQ})_{anode}} \qquad (4)$$

As a summary, it can be said that the main objective of the algorithm is to be able to test the batteries of an electric vehicle in an online, quick and easy way. The algorithm to develop will be based on partial charging or discharging at a fast rate. Cell full charge/discharge test are developed for developing the algorithm. Prior to the discharge, the cells are fully charged in CC-CV mode at 1C. The charge and discharge are performed at a C/5 rate. This Crate has been chosen as it was the fastest one that enabled observing the voltage plateaus in view of implementation in real application where low rate cycling is impractical. In addition, galvanostatic voltage profiles will be used for examining electrode phase changes and understanding degradation phenomena.

4 Algorithm development for Vehicle to Grid applications

There are many different approaches, algorithm types, methodologies and models to develop the status estimation of a battery. Nevertheless, due to the complexity of the objective estimation and the wide range of possibilities, a comparison between different learning methods for V2G applications has been done. Like this, the most fitting machine learning, or artificial intelligence technology should be used in order to develop the most suitable techniques for state estimation inside V2G applications.

4.1 Learning methods for V2G algorithms

- Extended Kalman Filter

A basic Kalman filter uses a series of measurements observed over time and selects the output variables that seem to be the more precise. It is a very accurate approach, nevertheless this filter can only operate with linear system. Due to this limitation, several variations and extensions have been developed inside the basic kalman filter approach. One of these non-linear approaches is the extended Kalman filter. In addition, this filter is quite known inside battery modelling. As an example, (17) uses tis filter to estimate the State-of-Charge (SoC) of a battery. In (18) not only the SoC, but also the OCV is estimated. In (19) the filter is used for SoH estimation by calculating the capacity and internal resistance of a cell.

The extended Kalman filter is a very nice solution for non-linear systems. The accuracy they get is quite high and the computational effort required is feasible for a bacis microcontroller. Nevertheless, there are already hybrid solutions in literature. The author of (20) proposes an enhanced closed loop estimator based on extended kalman filter. In order to estimate SoC. In addition, in (21) a combination of EIS internal impedance method and an extended kalman filter is proposed for SoH estimation.

- Unscented Kalman Filter

The unscented kalman filter is another possibility for non-linear systems. This filter estimates the result from different unknown variables to be more precise than those based on a single measurement. It has also been used to estimate SoC, SoH and even internal resistance (22). Due to the different evolution of the capacity decrease and the resistance growth in terms of time, both parameters are calculated separately. Accordingly, the parameters can be estimated separately, which means a less time-consuming exercise and a less computing effort.

- Genetic Algorithm

This methodology, Genetic algorithm, is frequently used in order to generate highly accurate responses on very diverse problems. This algorithm is inspired on biology and human interactions which can be relying on mutation and selection procedures. In 1960 John Holland introduced this new concept and afterwards in 1989 his student, David E. Goldberg, continued developing this algorithm.

The genetic algorithm is more and more used in battery state estimations. Current and voltage of the batteries can be directly measured, but the state estimations can be determined by means of a genetic algorithm. More concretely, SoH of the batteries and degradation mechanisms can be estimated. However, the genetic algorithm is difficult to implement online because of the high computational power required. Although using any other method it is difficult to implement it in an actual BMS (23).

- Particle Swarm Optimization

The Particle Swarm Optimization searches for a global optimization based on a memory computational algorithm able to play with different random solutions, accordingly, it is a random potential solution. This optimization moves through a multidimensional space consisting in the problem itself in a specific velocity (23). The particles are key because they can interact one to the other and adjust their moving velocity following movement patterns. This random movement of the particles help the search of the solution (local minima). In addition, inside this approach, each particle keeps track of their position in space (24). This algorithm has also been applied in battery state estimation, like in (25) where they estimate the SoC in real time by using particle swarm optimization. Additionally, it has also been used for battery sizing in a scenario including PV (26).

- Gaussian Process Regression

A gaussian process is a stochastic process, meaning a collection of random variables classified in time and space, in which any collection of those random variables will form a multivariate normal distribution, and can accordingly be normally distributed as a finite linear combination. One step further, from the continuous interference of values with a Gaussian process becomes the gaussian process regression. This form of algorithm has also been used in battery state estimation. In (27), a gaussian process regression is used for in situ capacity estimation of lithium ion batteries obtaining a 2-3% root mean squared error. Additionally, in (28) a random forest regression algorithm is used to evaluate the capacity of the battery with a comparison to the gaussian process approach, in order to compare the computational effort of both approaches.

4.2 Comparison of the different algorithms

The main objective of the algorithm is to generalize from the experience. This is what machine learning algorithms needs to do in order to perform accurately on new data basing their response in the obtained experience. The training usually comes from unknown probability distribution, in order to develop a generic model capable to produce accurate predictions for all new coming cases. Because of this core characteristics but considering that all described approaches differ from each other a comparison has been built. The algorithms are compared in different terms; accuracy, training time response time self-learning and linearity.

- Accuracy: Accuracy, precision and reliability are highly desired and quite complex to acquire. Nevertheless, getting the most accurate answer possible isn't always necessary. Moreover, through the use of linearly factored approximations to represent the value functions can be made arbitrarily close to the optimal. Nevertheless, the closer they are, the higher the final computational cost of the algorithm.
- Training time: Machine learning algorithms require the study and construction of algorithms that can learn from and make predictions based on their previous experience. The algorithm to develop aims to maximize its sample efficiency; this means that it requires fewer interactions with the environment in order to learn how to act. The training time still depends on the size and complexity of the environment.
- Response time: The response time is the total amount of time it takes to respond to a request for service. Once a policy has been learned, the algorithm requires applying Variable Elimination at each decision time-step to determine the optimal action to take. The complexity of this step depends on the graph made by the dependencies between the various agents and is generally exponential in the induced width of the graph.
- Linearity: Linear classification algorithms assume that classes can be separated by a straight line. These include logistic regression and support vector machines Linear regression algorithms assume that data trends follow a straight line. These assumptions aren't bad for some problems, but on others they bring accuracy down.
- Self-learning: is the ability of an algorithm to get more precise results in terms of time. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly.

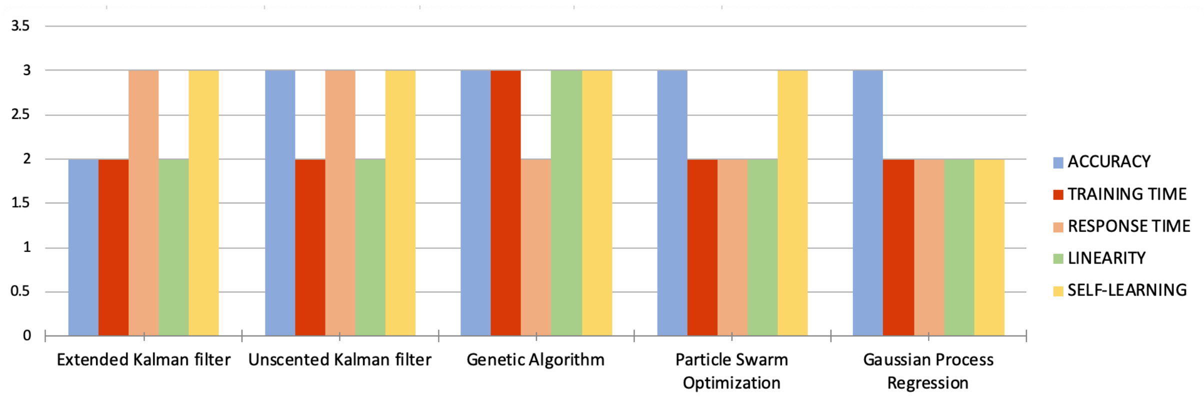

Figure 3: Accuracy, training time, response time, linearity and self-learning of the tested algorithms (29) (30) (31) (32) (33).

In figure 3, a comparison of the 5 algorithms can be seen. The graph shows that the lower score the less feasible and the higher score the most feasible and suitable it is for this algorithm to act best regarding the selected characteristics. The scores have been indicated for a V2G scenario, accordingly, for other possible applications these results may vary. Due to this, can be said that for this studied characteristic Gaussian Process Regression is the less suitable algorithm for a V2G scenario. On the contrary, Genetic Algorithm suits the best for all characteristics expect for response time, not scoring very high.

In addition to these characteristics, speed, predicting numeric capability, dimension reduction, simplicity and large data set performance will be studied in the chosen algorithms. In the same way as before, in order to understand the meaning of each parameter, a small introduction has been added.

- Speed: The number of minutes, seconds or milliseconds necessary to train a model varies a great deal between algorithms. The algorithm's complexity depends on the complexity of the problem and on how much time is allowed for batch updates between interactions with the environments. The algorithms can process tens/hundreds of timesteps per second, in environments with hundreds of agents.
- Predicting numeric: So far, we have considered mainly discrete representations for data and hypotheses in machine learning however, often find tasks where the most natural representation is that of prediction of numeric values
- Dimension reduction: The process of reducing the number of random variables in question, and the possibility if can be divided into function selection and function extraction.
- Simplicity: The balance between transparency and performance can be described as the relationship between research and real-world applications. There are many practical advantages to simplicity in machine learning models that can't be easily overlooked until you are confronted with a real world scenario.
- Large data set performance: The algorithm has several steps that can be parallelized, but the current implementation is single-threaded. The algorithm can either directly interact with the environment or work with replay buffers as well. In addition, different methods, react differently depending on the size of the data sets.

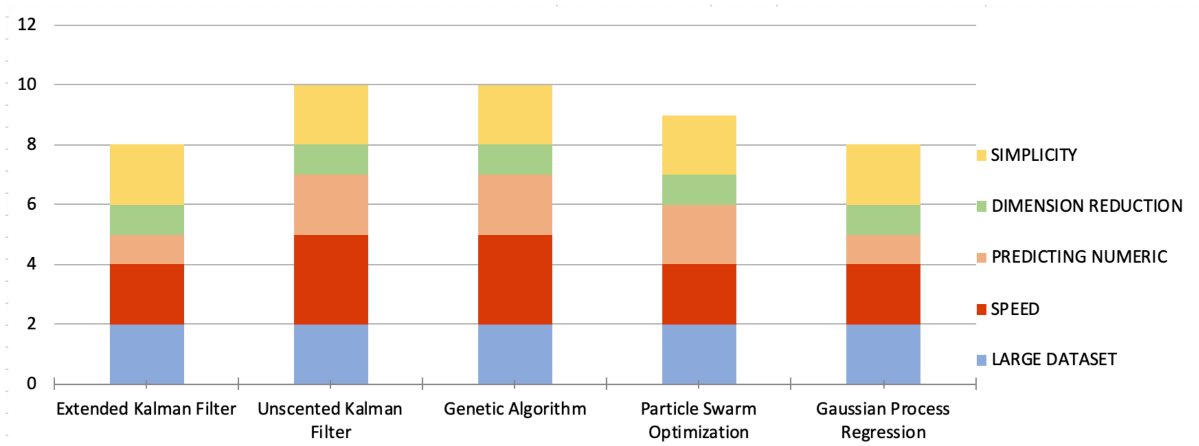

Figure 4: Speed, predicting numeric, dimension reduction, simple and large data set performance of the tested algorithms (29) (30) (31) (32) (33).

In figure 4, a comparison of the 5 algorithms can be seen. In the same way as before, the graph shows that the lower score the less feasible and the higher score the most feasible and suitable it is for this algorithm to act best regarding the selected characteristics. The scores have been indicated for a V2G scenario, accordingly, for other possible applications these results may vary. Due to this, can be said that for this studied characteristics Gaussian Process Regression and Extended Kalman Filter, in overall, are the less suitable algorithms for a V2G scenario. On the contrary, Genetic Algorithms and Unscented Kalman Filter suit the best for all characteristics making a notorious difference in speed.

4.3 Ranking

Overall, and covering all studied characteristics, a ranking of the algorithms has been developed. Nevertheless, it needs to be highlight once again that the scoring has been based in considering V2G as an application scenario, for other kind of applications this result may vary.

1- Genetic Algorithm: Very good in accuracy, training time, linearity and speed

2- Unscented Kalman Filter: Very good in accuracy, response time, self-learning and speed.

3- Particle Swam Optimization: Very good in accuracy and self-learning.

4- Extended Kalman Filter: Very good in response time and self-learning. Poor in predicting numeric.

5- Gaussian Process Regression: Very good in accuracy. Poor in predicting numeric.

5 Conclusions

Our contemporary society needs to fully decarbonize in order to tackle the climate crisis we are facing. Accordingly, we are in the need of using renewables energies. Unfortunately, renewable energy is intermittent, so an unbalance between demand and supply exists. The issue with e-mobility is the availability of electricity and the grid integration of the charging infrastructure. The onboard energy storage unit of the electric vehicle can act as energy buffer for the electricity grid when bidirectional chargers are deployed, and grid services are offered. Unfortunately, there are no real options to implement these possibilities at the moment.

In this regard, this paper presents a methodology so to develop a novel algorithm able to estimate the SoH online, accurately and non-aggressively. In addition, and in order to develop a smart and highly efficient algorithm a study on the most suitable algorithms for V2G application has been done. Inside the studied algorithms it can be found; extended Kalman filter, unscented Kalman filter, genetic algorithm, particle swarm optimization and gaussian process regression. As a result, genetic algorithm showcased the most suitable algorithm to be implemented in aV2G scenario. Accordingly, in order to develop a valuable, novel and key smart SoH estimation inside a V2G scenario both aspects need to be considered; the different concerns sated inside the methodology by using the most suitable algorithm, which seems to be in this case, the genetic algorithm. The methodology will be key in order to prolong a safe use of the battery inside a vehicle to grid application.

6 Future Work

This paper shows the first step of developing a smart, efficient and novel algorithm for SoH estimation inside V2G applications. As further steps, all the cited constrains will be taken into consideration so as to develop the real algorithm. This resulting algorithm will be tested and validated in the demo sites within different projects in which VUB is working now, such as OPTIBIDS. This project aims to develop intelligent smart and bi-directional charging strategies. In the project self-learning algorithms to predict short- and long-term power needs in accordance with the availability of electric vehicles in the local energy system will be developed. In addition, mobility patterns, charge preferences, vehicles state that enable LES operators to optimize their operational management will be considered. Accordingly, the resulting algorithm will be tested and validated in the demo sites within the project.

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Dr. ir. Maitane Berecibar obtained her PhD in Engineering of Sciences at the VUB on August 2017 named “Development of an Accurate State of Health Estimation Technique for Lithium-Ion Batteries”. The PhD was a collaboration between the Technology Research Centre IK4-Ikerlan, located in Spain, and the VUB inside the MOBI research group. During her studies she has also collaborated with other universities from abroad, like the New Jersey Institute of Technology (US), and the Brno University of Technology (CZ) developing the following projects “Estimating Storage Requirements for Wind Power Plants” and “Quality of Service of Free Space Optical Links”. Now as a senior researcher inside the VUB, she is very much interested in 2nd life batteries, vehicle to grid applications, microgrids and circularity, where she is focused on grant writing and project management.

Dr. ir. Cedric De Cauwer obtained his Master’s Degree in Engineering at the Vrije Universiteit Brussel in 2011, with a specialization in vehicle and transport technology. He immediately joined the MOBI research group to work on electric and hybrid vehicle technology. Since 2013, Cedric’s PhD research was funded by an IWT scholarship and focused on the prediction of energy consumption and driving range of electric vehicles, and energy-efficient routing. He obtained his PhD in 2017 and has since continued to apply his expertise in national and international projects.

Prof. Dr. Thierry Coosemans obtained his PhD in Engineering Sciences from Ghent University in 2006. After several years in the industry, he became a member of the MOBI research team at the VUB, where he works now as the ‘Electric and Hybrid Vehicle’ team leader. He is currently involved in the scientific support for the Green Energy Park Zellik, Flanders Make and had an active role in the Living Labs Electric Vehicles Flanders. On a European level, Thierry was and is involved in several H2020 and FP7 projects. His main research interests are electric and hybrid propulsion systems, performances of electric-vehicle fleets under real-life conditions, including in a V2G perspective, as well as the development of CO2-neutral Local Energy Systems.

Prof. Dr. ir. Joeri Van Mierlo leads the MOBI – Mobility, Logistics and automotive technology research centre. He is expert in the field of Electric and Hybrid vehicles (batteries, power converters, energy management simulations) as well as to the environmental and economical comparison of vehicles with different drive trains and fuels (LCA, TCO). He is the author of more than 500 scientific publications. He is editor in chief of the World Electric Vehicle Journal and co-editor of the Journal of Asian Electric Vehicles and member of the editorial board of “Studies in Science and Technology”, “Batteries” as well as of “ISRN Automotive Engineering”. He is Guest Editor of Special Issues “Rechargeable Battery Technologies–From Materials to Applications” of “Batteries” as well of “Advances in Plug-in Hybrid Vehicles and Hybrid Vehicles” of the “Energies” Journal.

Dr. ir. Maarten Messagie leads the LCA team of the research group MOBI at the Vrije Universiteit Brussel. Maarten develops and coordinates several large European and national projects on electric vehicles and microgrids successfully. His expertise and research focus is on the optimization of sustainable energy systems including electric vehicles, renewable power generation and energy storage systems.