TOWARDS ELECTRIC POWER TRAINS

- Fuel cell stack
- Converter
- Inverter
- Motor
- Battery
- VFC
- RFC
- IFC
- IS
- VFC
- Vbus
- Vbus
- VS
- RS
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Model based engineering and design of electric power trains

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Introduction

Since some decades now, the automotive industry focuses its development efforts on the reduction of exhaust gas emissions and fuel consumption. Over time remarkable results have been obtained, especially regarding the emissions of soot, NOx and hydrocarbons. Improvements in the combustion process for diesel and gasoline engines contributed to this success. Still, the efficiency of the total drive train of a regular vehicle leaves ample room for improvement. In city driving only about 10% of the energy available in the fuel is used for propulsion and power generation; the rest is wasted as heat. This is mainly caused by low part load engine efficiency, inefficient driving (late up shift), waste of brake energy and inefficient transmissions.

Since two decades, more and more OEM's develop hybrids to address these shortcomings. By making use of the high efficiency, high torque capacity and power density of electric motors, the efficiency of the drive trains was improved. Nowadays, also the electric vehicle, powered only by means of a battery, has become popular again.

As a general trend we see a continuous increase in the electrification of the automotive power train. This is accompanied with a steady increase in the electrification of the auxiliary systems, like the water pump and parts of the HVAC system. This holds for both light duty and heavy duty vehicles.

Recognizing this trend led HAN Automotive Research (HANAR) to initiate the RAAK-PRO Electric Power Train (EPT) project. The goal of this project was to answer the central research question: How can we model the components and subsystems of electric, hybrid and fuel cell vehicles such that the realization process of these vehicle can be accelerated and improved and how can these models assist in the development of the system control software? The modelling efforts should also pay off for our lecture material: cases treated in the classroom find their origin in the results of the EPT project.

This booklet gives an overview of the project activities that were undertaken to accomplish these goals. This chapter gives a management overview of all project activities, whereas the succeeding chapters give more in-depth detail on various subprojects.

Approach

Within the framework of the EPT project, several subprojects were undertaken, ranging from design studies of vehicle power trains and the realization of several test vehicles to a PhD research on the energy management of a fuel cell hybrid drive train. The EPT project was also used to assist other projects in order to improve the quality of the overall outcome. Examples are the Pluto project, for which models were constructed for the entire test rig and the H2ANCAR project, which produced the fuel cell hybrid Fiat HyDoblo vehicle. For this vehicle the energy management system was designed and tested successfully. These projects themselves provided the test facilities, needed for validation of the models created within the EPT project.

The subprojects of the EPT project are positioned inside the dotted box indicated by “Scope of EPT project” in Figure 1, which also shows the V-cycle method for product development in a simplified representation. This figure shows the relationship with other projects, which will all be described shortly in the following sections.

Overview of subprojects and related projects

Energy management for fuel cell hybrid vehicles

The motive for starting a PhD research on the energy management of fuel cell hybrid drive trains was two-fold:

i. ongoing worldwide developments in the field of the vehicle power train in the direction of further electrification (hybrids and electric vehicles);

ii. a number of companies in the region active in the field of fuel cells and hydrogen. Also the municipality of Arnhem advocates itself as "hydrogen city".

The subproject was undertaken in collaboration with the Faculty of Electrical Engineering of the University of Eindhoven, providing the promotor. Nedstack, a fuel cell manufacturing company in Arnhem,
supplied the fuel cells for testing and model validation, as well as in depth technical information. Silent Motor Company was a partner during the design and realization phase of the fuel cell stack systems.

The subproject has resulted in a PhD thesis [1], a number of journal publications and several congress contributions (see references in [1] and in chapter 2). The project activities have greatly enhanced the knowledge level at the HAN University with respect to fuel cell technology and fuel cell hybrid drive trains. The acquired knowledge was used for making new lecture material for both bachelor and master students. The development of the ARVAL Inspire II [2] by HAN bachelor students, greatly benefited from this research. The HAN organized two workshops on the basis of the acquired knowledge.

Chapters 2 and 3 present an overview of the scientific results that were obtained.

Results of this research were used for the realization the HAN HyDoblo Fuel cell vehicle. The vehicle was then used for validating the energy management strategy. The strategy was implemented in the vehicle controller by using the software development tools HANcoder and HANTune resulting from another subproject of the EPT project, described in the next section and in chapter 4.

During the research work on the energy management for fuel cell hybrid drive lines, a description of the power required for propulsion of the vehicle was needed. Simulations on hybrid propulsion systems generally use driving cycles to define the speed sequence of the vehicle. Disadvantages of this deterministic approach are the limited value of just one driving cycle to represent real-life conditions and the risk of ‘cycle beating’ in optimizations. Chapter 3 presents the results of a study into the modelling of the vehicle load in terms of normal distributions.

Battery hybrid electric vehicle rapid control prototyping platform

During the first phase of the EPT project, an already existing rapid control prototyping (RCP) platform initiative was further developed to become a safe, universal RCP platform for BHEV applications. This development was very well suited to be incorporated within EPT, since it is clearly based on model based design and resulted in tools that were of great value for implementing control strategies (like the above mentioned energy management strategy) in both vehicles and test rigs.

Partners during this phase of development were companies like Drive Train Innovations (now Punch Powertrain) for applications on the Pluto test rig and Silent Motor Company for fuel cell system applications.

The subproject resulted in the development of the ‘HANcoder RC30 Target’, a so called ‘embedded target’ for generating code from MATLAB/Simulink for a Rexroth RC30 series automotive specified controller (ECU). Also the development of an application engineering tool, named HANTune, to serve as a real time dashboard for the algorithm running in the RC30 ECU, was a result of this subproject. A pragmatically oriented handbook for applying the functional safety related procedures and methods as ISO26262 in electric power train control systems also originates from this subproject. The subproject also has important spin-off for education, since the tools are also used extensively in the minor ‘Autotronica’. Students are much less involved with direct coding and debugging of controller software, thereby saving time for model based design in real life applications. More details can be found in chapter 4.

These activities have formed the basis for the follow-up project Fast & Curious and, more recently, SMARTcode. An ever increasing number of SME’s use the tools and collaborate in a community. This community allows for a quick exchange of ideas and market driven product developments.

Duvel, CVT drive train modelling

In a later phase of the EPT project, it was decided to apply the tools and ideas developed during the first phase in a project together with Bosch Transmission Technology. The main research question was: what role can the Continuously Variable Transmission (CVT) play for the development of electric vehicles? The answer to this question was to be obtained by a modelling and simulation study, thereby making the relevance for the EPT project obvious. Several student groups (bachelor, master for thesis assignments and two minor groups) have been active for this research assignment. By using the AMEsim simulation package, students were able to simulate the various drive train variants with relative ease. Detailed efficiency models of CVT variator, electric motors, batteries and hydraulic systems were available, leaving the parameterization work and model structure design for the students.

The project work together with Bosch TT is part of a more comprehensive multi-year collaboration between a big TIER 2 supplier and the Automotive Centre of Expertise (ACE). This collaboration focuses on project work and on improved contact between the company and the students, being their potential future staff members.

The project resulted in a number of (thesis) reports that clarified the possible (dis-)advantages of a CVT for electric vehicle application. The reports also gave recommendations for improving the CVT performance on certain aspects, thereby making the CVT a more viable option. A typical example of a model used by some students is shown in Figure 3 [3]. In this figure, the battery, variator, electric motor, hydraulics, auxiliaries and various controllers can be identified.

The project activities have been reviewed intensively with Bosch engineers on a regular basis. The activities have led to the start of a follow-up project: noise measurement on a CVT on the Pluto test rig.

A prototype emission free cooling trailer

HAN Automotive Research was asked to contribute to the New Cool project, aiming at the development of an autonomous cooling trailer. The project was initiated by Twan Heetekamp Trailers in collaboration with TMC, TRTA, TPTS, VALX axes and TRS cooling systems. The New Cool trailer (Figure 4) powers the
cooling compressor from brake energy, solar power and from the grid. Both students and HANAR staff contributed to this development in the fields of energy management and rapid control prototyping. Also during the testing phase HANAR was involved. Experience and knowledge obtained during the EPT project proved to be of great value for this development. The project resulted in a fully functional trailer, showing good performance characteristics. Aspects for improvement, like component sizing and optimized energy management, were also identified. Results have been presented at the FISITA 2014 congress [4]. A summary of this paper is included in chapter 5.

Batteries play a central role in the drive lines of electric and hybrid vehicles. They are bulky, heavy, expensive, constitute a potential hazard, are very sensitive to temperature and have a limited durability, which in turn depends on aspects like depth of discharge, C-rate in charging and discharging and, again, temperature. All this calls for an in-depth study into the functional behaviour of automotive batteries. In collaboration with KEMA (now DNV-GL) and the HAN engineering department a research project was initiated, aiming at obtaining functional models of Lithium batteries. The research was focused on the electric and thermal behaviour. This work resulted in validated models in both MATLAB/Simulink and AMESim simulation environments. A battery simulator was developed (see chapter 6), which can be used for testing of battery management systems. The thermal modelling, described in detail in chapter 7, focused on the thermal behaviour on cell level, in interaction with its surroundings. As a result of this work we are now in a better position to design and test battery systems on board of vehicles and to make an assessment of the commercial viability of various solutions. As an example may serve the study on the efficiency of regenerative braking within the research project ‘eMobility-Lab’ of the Hogeschool Rotterdam [5].

Pluto test facility

The Pluto test rig (see Figure 5) has been designed and realised within the RAAK International project “Pluto”. This rig is very well suited to test all kinds of light duty electric drive trains. Within the EPT project we have focused on generating models for the test facility, that allow for the development of control software for the rig. During the control system development in Pluto, plant models have been developed for power train components and vehicle behaviour. These models have been used in various stages of the development, when no real power train hardware was available yet: at simulation level for early development of algorithms and in HIL simulation to test and optimize real-time behaviour of the control algorithms. Some more details can be found in chapter 4. Collaborating with companies like Drive Train Innovation (now Punch Powertrain) and Bosch Transmission Technology, we were able to finish this development and attract research assignments from these industries and others.

Colt test vehicle

An electric vehicle (Figure 6) has been developed. The municipality of Helmond financially supported this activity. Partners during this development were: HAN-Automotive, Fontys, ACE, ROC ter AA, TU Eindhoven and the companies All Green Vehicles, Nedcar, Panasonic, Sterr Autoschade, Awefflex, NXP, Van den Heuvel Motorsport and TNO Automotive. The vehicle was used by TNO for the test of measuring equipment. NXP used the vehicle to test their new Battery Management System. The vehicle has been optimized for use in bachelor and master courses. Several students have participated in the development activities. The vehicle was also used at several occasions for promotional purposes.

Conclusions and outlook

The RAAK-PRO Electric Power Train project has been very successful in providing the means to extend and disseminate our knowledge in the field of battery electric, hybrid and fuel cell drive trains. Results of the project have been transferred to numerous projects with many partners. Several examples of these projects are shown in this booklet.

By using high level simulation tools like MATLAB/Simulink and AMESim, models were derived for fuel cells, batteries, electric and hybrid vehicles and the Pluto hybrid drive train test facility. These models were very important during both the design and the testing phases of the various products we worked on.

The models have found their way also in the curriculum offered to bachelor and master students. In turn, many students contributed to the realization of the models during internships and thesis work.

Results from the RAAK-PRO Electric Power Train project will be used in ongoing and future projects with a focus on power train development. An extension of the application area to industrial applications has been undertaken in running projects in the field of model based design (Fast & Curious, SMARTco.de). Another extension towards agricultural applications is currently under investigation. Activities for automotive companies (DAF Trucks, Bosch TT, Bosal, etc.) are carried out, which greatly benefit from the knowledge acquired and hardware developed during the EPT project.

The RAAK-PRO Electric Power Train project has made the HAN Automotive Research group a more valuable partner for all of its stakeholders: teachers, companies, staff and students.

Acknowledgements

The work described in this booklet would not have been possible without the support of numerous students, who contributed during minor projects, internships and thesis assignments. The financial support from the RAAK-PRO program is gratefully acknowledged. Numerous companies and institutes have contributed to the EPT project: Nedstack, Bosch Transmission Technology, Drive Train Innovations (now Punch Powertrain), Silent Motor Company, APTS, e-Traction, Spijkstaal Electric BV, TU Eindhoven, Hogeschool Rotterdam, Fontys Hogescholen, KEMA (now DNV-GL), LMS International (now Siemens) and Dutch-INCERT. Their contribution, either as member of the project consortium or by providing technical support is gratefully acknowledged.
Analytic solution to the energy management problem for fuel cell hybrid vehicles

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Abstract

As fuel cell hybrid propulsion systems comprise energy storage, an energy management strategy is needed for proper control. Objective of such strategy is to deliver the demanded power for traction with a minimum hydrogen consumption. This paper discusses an analytic solution to this optimization problem, based on the minimization of losses in the propulsion system. This analytic solution enables a real-time implementation. It has been validated through simulations and measurements on a 10 kW test facility and on road in a fuel cell hybrid vehicle. Simulations show the presented solution performs within 2% of a benchmark derived off-line by dynamic programming and brute force calculations. Experiments confirm this fuel consumption and demonstrate its practical value.*)

1. Introduction

Fuel cell hybrid power trains comprise an energy storage to supply peaks in the power demand and to facilitate regenerative braking. In terms of control systems, the presence of storage provides additional freedom to minimize the vehicles’ fuel consumption. The approach to this control challenge is generally referred to as the Energy Management Strategy (EMS).

Several energy management strategies are proposed in literature, based on fuzzy logic [1], efficiency maps [2], classic control [3] or rule-based [4]. Also efforts are made to model the fuel consumption as a cost function and to find the minimum in this cost function using different techniques, such as dynamic programming [5]. Analytic solutions are found for comparable applications as alternator optimization [6] or internal combustion engines [7, 8]. These analytic solutions represent the power from the battery with equivalent costs, resulting in an Equivalent Consumption Minimization Strategy (ECMS). As models, an efficiency as zeroth order battery model, and a quadratic representation of the fuel consumption, are used [6, 7, 8]. In [9] this approach is extended to a first order battery model, with a cost function based on physics to express the fuel consumption. An extensive overview of publications on EMSs for fuel cell hybrid vehicles is provided for in [10].

This study minimizes the fuel consumption using an alternative approach. Where most studies focus on the level of power, this study shifts one level of detail further, to voltages and currents. In addition, not the fuel consumption is minimized, but the losses in the power train. A minimum in losses is the equivalent to a minimum in fuel consumption. The result provides an analytic solution expressed in measurable variables and physical parameters.

The solution found corresponds to the solution presented in [14, 15]. This paper presents the derivation of the analytic solution to the energy management problem in terms of voltages and currents, and its validation through simulation and measurements.

*)This paper contains parts and partly summarizes content of [14] and [15].

References

2. Problem definition

Objective of the energy management strategy is to minimize the losses in the fuel cell hybrid propulsion system, without compromising the drivability of the vehicle. This minimum in losses matches the minimum in fuel consumption.

The considered topology of the propulsion system is presented in figure 1. It comprises a fuel cell stack subsystem as primary power source, a battery for energy storage, a DC/DC converter to match voltage levels and an inverter to provide alternating current to the motor. The fuel cell stack subsystem includes auxiliaries as an air compressor, hydrogen control valve, recirculation pump, humidifier and cooling system. Hydrogen as fuel is derived from a hydrogen storage tank.

3. Models

The fuel cell stack converts hydrogen into electric power. A polarization curve defines the relation between stack voltage and stack current. Figure 2 presents a typical polarization curve. Under normal operating conditions, both the activation area (A) and the concentration area (C) are avoided. In area (B), the ohmic losses dominate the total internal losses. For this operating area, the fuel cell stack acts as an internal voltage source \( V_{FC} \), which is represented by an ideal voltage source \( V_{FC0} \) with an internal resistance \( R_{FC} \) as indicated in figure 1. The resulting voltage at the terminals of the battery equals:

\[
V_s = V_{FC0} - R_s I_s
\]

As a result, the power losses in the battery equal \( P_s R_s \).

The DC/DC converter matches the fuel cell stack voltage \( V_{FC} \) with the bus voltage defined by the battery voltage \( V_S \). This conversion introduces a small loss, expressed in a converter power efficiency \( \eta_{cnv} \) (<1):

\[
I_{cnv} V_S = \eta_{cnv} I_{FC} V_{FC}
\]

The converter converts the fuel cell stack current \( I_{FC} \) to a net current \( I_{cnv} \) according to a ratio \( r \):

\[
I_{cnv} = r I_{FC}
\]

with ratio \( r \) is defined by the voltages and converter efficiency according:

\[
r = \frac{\eta_{cnv} V_S}{V_{FC}} = \frac{V_{FC} - I_{FC} R_{FC}}{V_{FC} - R_s I_s}
\]

Over time, the average battery current has to approach zero to avoid depletion and overcharging. Assuming sufficiently small excursions for the fuel cell stack current and battery current, the ratio \( r \) is approximated with:

\[
r \approx \frac{\eta_{cnv} V_S - I_{FC} R_{FC}}{V_{FC}}
\]
As a result, ratio \( r \) is a constant in the optimization. For the experiments discussed later, the maximum instantaneous error made due to this approximation is maximum 13%, at the upper boundary of the propulsion systems operating window (maximum battery current).

The total current delivered by the fuel cell stack and battery has to provide the current \( I_p \), needed for propulsion and the current \( I_{aux} \), needed for the auxiliaries. Especially, the air compressor significantly contributes to the current demand of the auxiliaries. As the oxygen consumption of the fuel cell system is proportional to the stack current, and assuming an air compressor current proportional to its air mass flow, the current \( I_{aux} \) to operate the auxiliaries is approximated by:

\[
I_{aux} = \gamma I_{FC} + I_{aux0}
\]  

(7)

Here, \( I_{aux0} \) defines the offset and \( \gamma \) the proportional part of the stack current needed for the auxiliaries. This relation is verified on the test facility as an acceptable approximation [14].

4. Analytic solution

The losses in the propulsion system are dominated by the internal losses in the fuel cell stack, the losses in the battery and the losses in the converter. Based on the model equations of the previous chapter, these losses are expressed in a cost function (8). In this cost function, the losses in the DC/DC converter are implicitly included in the battery current, and the current to the auxiliaries is considered part of the total current demand. The control variable in this cost function, available to minimize the cost function, is the fuel cell stack current IFC, defined by the control signal to the DC/DC converter.

\[
f(I_{FC}) = \int_{t_0}^{t_f} \left( \frac{1}{2} I_{FC} R_{FC} + I_{aux} R_g \right) dt
\]

(8)

This cost function is subject to two constraints: the total current demand should be met (9), and the battery should not be depleted nor overcharged. This latter constraint is stated more stringent as a zero difference in the State Of Charge (SOC) between the end and the start of the driving cycle (10). This guarantees a continuous valid operation of the battery, and enables comparison between different energy management strategies.

\[
(r - \gamma) I_{FC} + I_a + I_{aux0} = 0
\]

(9)

\[
\int_{t_0}^{t_f} I_a dt = 0
\]

(10)

As constraint (9) represents a linear relation, it is used to reduce the number of equations. The optimization problem of finding the minimum in cost function (8) subject to constraints (9) and (10) is solved analytically by converting cost function \( J \) into a Lagrangian \( L \) by combining the constraint (10) on the SOC with cost function (8) using a Lagrange multiplier \( \lambda \) [11, 12]:

\[
L(I_{FC}, \lambda) = \int_{t_0}^{t_f} \left( \frac{1}{2} I_{FC} R_{FC} + I_a + I_{aux0} - (r - \gamma) I_{FC} R_g \right) dt + \lambda \left( I_a + I_{aux0} - (r - \gamma) I_{FC} R_g \right)
\]

(11)

To ensure that a minimum is found in the Lagrangian \( L(I_{FC}, \lambda) \), small random deviations towards variables should not result in deviations in the Lagrangian. As necessary conditions for this minimum, the derivatives towards variable \( I_{FC} \) and the introduced Lagrange multiplier \( \lambda \) have to be zero:

\[
\frac{\partial L(I_{FC}, \lambda)}{\partial I_{FC}} = 0
\]

(12)

\[
\frac{\partial L(I_{FC}, \lambda)}{\partial \lambda} = 0
\]

(13)

The second necessary condition (13) just returns the constraint on the SOC (10). The first necessary condition (12) provides the optimal solution \( I_{FC}^{*}(\gamma, \lambda) \), as function of the Lagrange multiplier:

\[
\frac{\partial L(I_{FC}, \lambda)}{\partial I_{FC}} = \int_{t_0}^{t_f} \left( 2 I_{FC} R_{FC} - 2 (r - \gamma) I_a - (r - \gamma) I_{FC} R_g \right) dt + \lambda \int_{t_0}^{t_f} - (r - \gamma) dt
\]

(14)

A solution for which this necessary condition (14) is zero equals:

\[
2 I_{FC} R_{FC} - 2 (r - \gamma) I_a - (r - \gamma) I_{FC} R_g - \lambda (r - \gamma) = 0
\]

(15)

This relates the optimal stack current \( I_{FC}^{*} \) to Lagrange multiplier \( \lambda \) as:

\[
I_{FC}(\lambda) = \frac{2 I_{FC} R_{FC}}{R_{FC} + (r - \gamma)^2 R_g} \left( I_a + I_{aux0} \right) + \frac{1}{2} \frac{(r - \gamma)}{R_{FC} + (r - \gamma) R_g}
\]

(16)
Combining both constraints (9) and (10) with relation (16) provides an analytic solution for $\lambda$:

$$\int_{t=0}^{t_f} I_d + I_{aux} - (r - \gamma)I_{FC}(\lambda) \, dt = 0 \tag{17}$$

Subsequently:

$$\int_{t=0}^{t_f} I_d + I_{aux} - (r - \gamma)\frac{(r - \gamma)R_e}{R_{FC} + (r - \gamma)^2R_s} (I_d + I_{aux}) + \frac{1}{R_{FC} + (r - \gamma)^2R_s} \, dt = 0 \tag{18}$$

and:

$$\int_{t=0}^{t_f} \frac{R_{FC}}{R_{FC} + (r - \gamma)^2R_s} (I_d + I_{aux}) + \frac{1}{R_{FC} + (r - \gamma)^2R_s} \, dt = 0 \tag{19}$$

result in:

$$\int_{t=0}^{t_f} \frac{1}{2}(r - \gamma)^2 \lambda \, dt = \int_{t=0}^{t_f} R_{FC}(I_d + I_{aux}) \, dt \tag{20}$$

In (20), $\lambda$ and $I_d$ relate only by their average value. This reduces the need for a-priori information on the driving cycle to only the future average current demand. The resulting optimal value for a constant $\lambda$ becomes:

$$\lambda = \frac{1}{2} \frac{(r - \gamma)^2}{R_{FC} + (r - \gamma)^2R_s} \tag{21}$$

Combining this solution (21) for $\lambda$ with (15) results in the optimal control variable $I_{FC}^*$ as analytic solution to the optimization problem:

$$I_{FC}^* = \frac{(r - \gamma)R_s}{R_{FC} + (r - \gamma)^2R_s} (I_d + I_{aux}) + \frac{1}{R_{FC} + (r - \gamma)^2R_s} (I_d + I_{aux}) \tag{22}$$

or

$$I_{FC}^* = \frac{1}{r - \gamma} (I_d + I_{aux}) + \frac{(r - \gamma)R_s}{R_{FC} + (r - \gamma)^2R_s} (I_d - I_d) \tag{23}$$

A closer observation of solution (23) reveals the optimal stack current consists of a constant part, related to the average current demand, and an instantaneous part, related to the deviations in the demanded current. This instantaneous part is split over fuel cell stack and battery, according to their internal resistances (23). Expressing this constant power split ratio as $\Phi$, and introducing $\Delta I_d$ as the deviations in the current demand, results in the next expression for optimal control:

$$I_{FC} = \frac{1}{r - \gamma} (I_d + I_{aux}) + \frac{1}{r - \gamma} \Phi \Delta I_d \tag{24}$$

with

$$\Phi = \frac{(r - \gamma)^2R_s}{R_{FC} + (r - \gamma)^2R_s} \tag{25}$$

5. Implementation

The constant part of (24) is considered the point of operation for the fuel cell stack, from which the fuel cell stack current changes according to the variations in the current demand and the value of the power split ratio. When, over a significant time horizon, the SOC of the battery decreases or increases, the point of operation has been too low or too high respectively. Essentially, the average future current demand is predicted by the average past current demand. Therefore, the point of operation of the fuel cell stack can be considered the result of a feedback loop on the SOC of the battery. This results in the real-time implementation as indicated in figure 3. This implementation comprises a slow feedback loop, providing robustness on the SOC, and a fast feed forward path, enabling a minimal fuel consumption.

![Figure 3. Fuel consumption minimizing EMS as combined feed forward path and feedback control loop.](image)

The rated maximum and minimum currents of both the fuel cell stack and battery are not considered as bounds in the optimization. Still, it can be proven that the specified bound is the optimum choice when such bound is exceeded. As consequence, the point of operation of the fuel cell stack has to be corrected, but thanks to the feedback loop on the SOC, this issue is covered such that optimality is still achieved.
6. Validation
The proposed EMS is validated through simulations and measurements. For simulations, validated models of an existing distribution truck are used (figure 4a). Measurements are taken on a 10 kW fuel cell stack test facility (figure 4b).

For comparison, also other EMSs are evaluated, such as the Range Extender approach (RE), ECMS and off-line Dynamic Programming (DP). RE refers to a constant fuel cell stack current. DP is based on full available knowledge on the future driving cycle. Therefore, its results are considered a benchmark for the smallest possible fuel consumption. Results for the proposed Analytic Solution are referred to as AS. Results for simulations over three driving cycles [13] are presented in table 1. Real-time results from experiments at the test facility are presented in table 2.

The accuracy of the test facility and repeatability of experiments is such that conclusions on the fuel consumption can be drawn with a significance of 0.1%. This high accuracy is obtained thanks to the very predictable performance of the fuel cell system and the use of an SOC model running in parallel with the actual battery.

It is concluded that AS provides a real-time strategy that performs slightly better compared to ECMS and closely approaches the benchmark for the possible minimum in fuel consumption. The complexity of AS is comparable to RE. Both methods are much less complex compared to ECMS and DP.

The Analytic Solution as EMS is demonstrated on-road using the fuel cell hybrid vehicle of figure 5. This EMS in this vehicle operated over 1.5 years with different drivers with a 100% availability.

7. Conclusions
The proposed minimization of losses provides an analytic solution to the energy management problem of a fuel cell hybrid propulsion system. The resulting EMS enables a minimum in fuel consumption, close to the global minimum. The assumption that the future average current demand is predicted by the past average current demand enables real-time implementation. In simulations and experiments, the proposed real-time EMS results in a fuel consumption within 2% of the minimum fuel consumption calculated as benchmark off-line using dynamic programming.

The proposed EMS has some additional benefits. Thanks to the comparable first order behavior of fuel cells and battery cells, the resulting analytic solution is simple and robust against parameter variations and disturbances. Apart from these benefits, an analytical approach provides a more fundamental understanding of the energy management problem of fuel cell hybrid propulsion systems.
References


Distribution of the power for traction for fixed gear electric propulsion systems

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Abstract

Most studies on power train design rely on deterministic driving cycles to define the vehicle's longitudinal speed. Especially simulations on hybrid propulsion systems use driving cycles to define the speed sequence of the vehicle and backwards calculate the power for traction. Disadvantages of this deterministic approach are the limited value of one driving cycle to represent real-life conditions and the risk of 'cycle beating' in optimizations.

Observations suggest that the distribution of the power for traction is more easily characterized than the distribution of the speed, as it tends to a bell-shaped curve. This study proposes to approximate this bell-shaped distribution with a normal distribution for electric propulsion systems with a fixed gear ratio. This proposal is motivated from simulations, chassis dynamometer experiments and real-world data. *

1. Introduction

As hybrid power trains comprise a storage, it is not sufficient to size the power train components on specifications as acceleration time and top speed only. Therefore, many design studies on hybrid power trains use driving cycles - time sequences of speed samples (m/s) - as input to simulations that define the required power for traction (W) [1, 2]. Such simulations are used for component sizing [2-6] and the design of energy management strategies [7-12]. For different vehicle classes and purposes, general accepted driving cycles are available. Examples are the NEDC for passenger cars, the FTP75 and JE05 for light and heavy duty vehicles in an urban environment and the Braunschweig, NYbus and Beijing Bus cycle for buses [13, 14]. As most of these cycles were initially developed for emission tests, initiatives as the LA92/UCDS as successor of the FTP75 [13], the ARTEMIS project [15, 16] and others [17] intend to provide cycles more suitable to modern requirements as a minimum fuel consumption. These driving cycles provide useful deterministic requirement definitions for several applications, including hybridized propulsion systems. Still, the cycle chosen will never be driven in real life [18]. They fall short when designing actual power trains. Therefore, sizing the system components and engineering the vehicles' energy management system need a better and richer cycle definition for specific vehicle and traffic circumstances, less depending on a deterministic series of speed points [19, 20]. For energy management systems, one approach to reduce this cycle dependency is to include an online cycle prediction. Such a prediction can be based on statistics and historic data [21], on GPS and navigation data [21, 22] or on dynamic traffic routing information [23, 24]. Prediction can help to increase the performance and robustness of the energy management system, but it does not support the sizing of the components in the design phase. For sizing, a characterization less depending on a predefined speed sequence is needed. Considering characterization for design, techniques are proposed as fuzzy logic and neural networks [18, 25, 30], time series analysis [26] or statistics based methods as principle component analysis (PCA) [27]. In [28], a method is presented that generates random driving cycles with statistical and stochastic properties similar to a driving cycle provided as 'seed' to the driving cycle generator. This reduces the risk of 'cycle beating' in design optimization. In a broader context, characterizations for other purposes

*) This paper contains parts and partly summaries [33] and [36].
are presented, such as the characterization of driving styles [29, 30]. The methods and approaches discussed consider a driving cycle as a sequence of speed samples over time (m/s). Still, propulsion systems have to provide the power for traction (W). Therefore, this study explores if a characterization of driving cycles in terms of power for traction is an attractive alternative.

Objective of this document is to motivate that the statistical distribution of the power for traction for an electric propelled vehicle, driven by a human, tends to one bell-shaped distribution. Such power distribution can cover a complete class of driving cycles. In addition, the paper proposes to approximate this distribution with a normal distribution. The parameters of such distribution are linked to vehicle parameters and some key characteristics of a driving cycle representing the traffic environment. The paper provides this relation using a general vehicle model.

2. Observations

2.1 First observations

Experiments and simulations with different vehicles, different driving cycles and different conditions resulted in substantial data of speed and power for traction. This data has been obtained from a delivery van (Fiat Doblo), a mid-size distribution truck (Hytruck) [6] and an articulated trolley bus. Although different, these vehicles have an electric propulsion system with one fixed gear in common.

From these experiments, three examples are presented, with their speed profile, and statistical distributions of speed and power for traction:

- Figure 1 shows a trip of the delivery van through a suburban traffic environment, where both speed and power for traction are measured through the logging system on the vehicle. This trip has a duration of 3165 seconds, an average speed of 43.1 km/h and a maximum speed of 82.0 km/h.
- Figure 2 shows a driving cycle of the articulated trolley bus in an urban area, where the speed is measured and the power for traction is derived through a vehicle model. The duration of this driving cycle is 4337 seconds, with an average speed of 25.8 km/h and a top speed of 81.9 km/h.
- Figure 3 presents simulation results where the JE05 standard is used as driving cycle, representing a mix of urban and suburban traffic conditions as traffic environment [13]. The power distribution is derived through a vehicle model of the midsize distribution truck, validated on component level [6]. The JE05 driving cycle has a duration of 1829 seconds with an average speed of 27.3 km/h and a top speed of 87.6 km/h.

In spite of the differences in vehicle class and the significant differences in speed distributions, the distributions of the power for traction show some resemblance. All experiments provide bell-shaped distributions for the power for traction.

For comparison, the normal distributions based on mean and variance of the considered data are included as curve in the graphs. But as the experiments cover a relative short time, resulting in an average number of samples per bin less than 70, the significance of these observations is not sufficient to draw final conclusions on the shape of the distributions. Therefore, experiments resulting in more data samples were initiated.
2.2 Long-term measurements

To cover the short observation time in the previous examples, an additional experiment was conducted, where measurements of both speed and power for the delivery van were logged over several days of operation. The resulting distributions are presented in figure 4 with the standstill/idling times skipped from the data.

The experiment includes rides in the city, the suburbs and the countryside. Where the distributions presented in the previous examples refer to flat terrain, the distributions of figure 4 include trips in some more elevated terrain.

This experiment, including over six hours of driving, supports the suggestion that, over a longer time horizon, the distribution of the power for traction is bell-shaped, with as exception a spike at zero power.

2.3 Chassis dynamometer results

To verify if such a bell-shape distribution also holds for predefined styled driving cycles as the NEDC, a comparison is made between the NEDC as simulated driving cycle and the NEDC tested on a roller test bench using the delivery van [31]. The NEDC Low Power version is used to reflect the capabilities of the vehicle considered. Figure 5 presents the results for simulation and figure 6 presents the results derived from the roller test bench.
Clearly, the simulated case does not result in a bell-shaped distribution, as the number of samples is limited and as the NEDC Low Power driving cycle is artificially constructed. The measured speed distribution resembles the original NEDC Low Power cycle: the dominant velocities are still clearly visible. However, the power distribution is much more blurred, suggesting a tendency towards a more bell-shaped distribution.

To evaluate the difference between a real-world driving cycle and an experiment on the roller test bench, the measured driving cycle of figure 1 is replayed on the chassis dynamometer. The results are presented in figure 7. Except for a spike around 8 kW, both speed and power distribution resemble the results of figure 1. This indicates the roller test bench is useful to represent real-life conditions with respect to speed and power distributions.

3. Motivation for a normal distribution

Both in measurements, roller test bench experiments and simulations and for different vehicles, the distributions of the power for traction show bell-shaped curves, especially when driving cycles with a significant duration are evaluated. When considering sizing the components of a propulsion system, a much longer time is relevant: the lifetime of the vehicle. Extending the horizon of observation to the lifetime of the vehicle, it is stated that the distribution of the power for traction is bell-shaped, with a peak around zero due to idling. Steady power consumption by auxiliaries or electric heating would shift this peak to non-zero values. With respect to the shape of the distribution, it is postulated that:

Over the lifetime of the vehicle, the distribution of the power for traction is sufficiently accurate approximated by a normal distribution.

A peak at zero to represent idling might be included when convenient. Coasting will not introduce a peak as will be explained later.

To provide some support for the hypothesis for a normal distributed power for traction, a first qualitative motivation is presented in this chapter. This motivation is based on a combination of driver behavior and vehicle properties, as indicated in figure 8.

The observation that the power for traction is the result of a low pass dynamic system supports the hypothesis of a normal distribution, as low pass systems provide normal distributed outputs on arbitrary distributed random inputs.
Still, the motivation for a normal distribution is an observation supported by arguments, rather than a proof. The vehicle itself is a nonlinear dynamic process. This hinders a mathematical proof: Unlike linear input-output relations, nonlinear properties result in higher order harmonics at the output. Therefore, an ultimate low pass behavior cannot be guaranteed.

Variables as wind speed and road inclination can be considered disturbances in the control loop. Over the lifetime of the vehicle, also the number of passengers and amount of payload can be considered disturbances. As several of these disturbances are uncorrelated, over time, based on the Central Limit Theorem, these disturbances further support a normal distribution of the power for traction.

### 4. Discussion

To further investigate the validity of the normal distribution hypothesis, measured data from electric propelled vehicles over longer periods of operation with a sufficient high sample rate should be available. As such data is not available yet, the hypothesis should be considered a reasonable assumption.

The motivation for a normal distribution relies on the feedback loop of figure 8. When this control loop is interrupted, the motivation for a normal distribution partly fails. This is the case during coasting (the driver releases the accelerator pedal and just accepts the resulting speed change), during gear shifting (again the accelerator pedal is released and for a short moment the power for traction reduces to zero or possibly a constant power level). Also when the driver shifts to mechanical braking, the loop is interrupted. First generation electric vehicles tend to implement braking to resemble the brake behavior of gasoline cars, but we observe a shift to maximum regenerative braking on the electric motor, or driver adjustable amount of regenerative braking. This improves the electric efficiency of the car and therefore its driving range. Examples are the BMW i3 commercial vehicle (maximum regeneration) and the Škoda Octavia green E line concept car (adjustable regeneration).

To evaluate the impact of gear shifting and mechanical braking, experiments are carried out with an electric concept vehicle with a 5-shift gearbox. In addition, the inverter is reprogrammed such that the accelerator pedal imitates the behavior of an ordinary gasoline vehicle: When released, only a small amount of power is regenerated from the kinetic energy of the vehicle, mimicking coasting. In addition, the drivers could use the 5-shift gearbox as in a conventional vehicle. With these adjustments, a commuter trip of approximately 40 minutes is made in an urban environment.

The results are presented in figure 9. Compared to the previous bell-shaped power distributions, this figure shows an additional peak at the negative “accelerator pedal released” power, and the resemblance with a normal distribution is diminished. Apparently, the driver’s behavior is affected by the programmed behavior of the accelerator pedal. This was confirmed by the test drivers. These results support the control loop as a model for the interaction between driver and vehicle and the closed loop assumption where the driver continuously controls the power for traction. This is also in line with the simulation results of figure 5, where the power for traction is the result of a single backwards relation, instead of a control loop.

### 5. Conclusions

The objective of this study was to evaluate if characterizing driving cycles by their power for traction is acceptable and beneficial. Experiments with different electric vehicles on the road, on a chassis dynamometer and in simulations, show that the distributions of the power for traction tend to be bell-shaped. Next, it is motivated this shape is acceptable approximated with a normal distribution.

A normal distribution is defined by its mean and variance. This mean and variance are directly linked to the vehicle parameters and key properties of the considered driving cycle. As a result, the power distribution not only represents the considered driving cycle, but more general the vehicle in a traffic environment for which the considered driving cycle is one observation. Therefore, representing the requirements for a vehicle in terms of a power distribution is more convenient than using one or a limited set of deterministic driving cycles.

![Figure 9. Measured distributions under gasoline vehicle imitating conditions.](image-url)
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Rapid control prototyping platform for electric and hybrid vehicle drive lines

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Abstract

This article describes the development of a Battery Hybrid Electric Vehicle (BHEV) RCP Platform in the light of the RAAM-PRO project Electric Power Train (EPT). During the first phase of EPT, an already existing platform initiative was further developed to become a safe, universal RCP platform for BHEV applications, ultimately usable for series production developments. This development was accompanied by the development of a ‘Functional Safety Handbook’ in order to comply with ISO26262 related procedures and methods when applying the platform in BHEV applications. As the platform development proceeded, it became clear that this technology became useful in a wider variety of applications as several HAN partners and clients expressed interest in the solution. As a result, new development requirements did arise, surpassing those of the EPT project, not only because of the wider application range but also because of the required development investment. Therefore, further development of the platform was moved into a separate project, called Fast & Curious. Fast & Curious focuses on a universal RCP platform for SME’s and HAN, in both R&D and educational settings. Beyond Fast & Curious, the project SMARTcode is now aiming series product development of control systems, including the development of a recommended practice according to ISO26262. With Fast & Curious and SMARTcode the original goals of EPT have been extended towards a wider application arena and a larger user base in the form of a growing community of companies and institutes, while still acknowledging the validity of the original development goals.

1. Introduction

Rapid Control Prototyping - or RCP - is a relevant development step on the left side of the V-cycle requiring the correct software tools in order to automatically generate code from a model. This code should be generated into a widely applicable, re-usable hardware platform. Market solutions exist, but are highly expensive and therefore not feasible in the HAN R&D environment where educational usage is essential and SME’s form a significant part of the customer base.

For this reason, HAN initiated the in-house development of an RCP solution preceding the EPT project. This development was further strengthened by defining it as one of the technical focus areas of the EPT project. During the EPT project, goals were formulated to realize an RCP solution in the form of a “BHEV RCP Platform” with the ultimate future goal to extend the platforms’ usability for series production usage. Series products need to be certified; therefore the development process of the products should comply with standards and regulations. In this respect, the ISO26262 standard [1] concerning functional safety in automotive E/E systems is one of the key guidelines to follow. Electric power trains can generate high torque instantly, potentially leading to danger, and this could occur due to a failure in the BHEV RCP Platform. Because of the complexity of the required processes, procedures and methods in ISO26262, the initiative was born to develop a handbook for applying ISO26262 in the scope of the electric power train application area targeted at SMEs.

2. Model based development V-cycle

The standardized V-cycle as defined in parallel in Germany and the USA covers system level requirements and design, followed by decomposition into sub-system and components on the left side, ending up in component implementation down at the bottom. On the right side a verification and validation takes place, with an upwards integration or re-composition from sub-systems up to system level.

When looking at model based development techniques for the development of control systems - or E/E systems in general - a simplified V-cycle can be derived, allocating the different primary use cases of model based development in the left and right side of the V-cycle, covering respectively specification and design on the left and verification, validation and optimization on the right (Figure 1).

Note that this V-cycle is not discriminating in system, sub-systems and components levels. The mentioned steps can be applied to all integration levels.

On the top left simulation is used for the first design and development. Simulation allows for setting up a plant model in conjunction with a controller algorithm. This enables deeper understanding of system and controller behaviour and allows for refining control strategies in a very early stage. Due to the gained knowledge in detailed system behaviour, this step can be - and normally is - used to refine requirements on all integration levels.

Since models are the key elements in model based development, the automatic generation of code from these models can significantly enhance the efficiency and effectiveness of the development process. It enables the 3 central steps in the abovementioned V-cycle:

- **Rapid Control Prototyping**, where code from the control algorithm model is automatically generated for a universal RCP control unit;
- **Implementation**, where code is again automatically generated from the control algorithm model. In this case the code is generated for the series production system so either the model has to be extended with aspects like robustness and diagnostics, or the generated code has to be combined with other code comprising these necessary aspects for series products;
- **Hardware In The Loop (HIL) testing**, where code is generated from plant models and executed on a computer system capable of running the models in real-time: a HIL simulator. With the correct input and output interfacing, a HIL simulator can electrically simulate a system to the level that control system can be connected to the HIL simulator as it is connected to a real world system. This enables reproducible, 24/7 conductible automated testing and validation of the control system behaviour.

![Figure 1. ‘Model Based Development V-cycle’](Image)
The BHEV RCP Platform is primarily intended for RCP as its name implies, but ultimately the solution is also intended for usage in series products, covering the implementation phase as well when this solution becomes available. Obviously, much of the automatic code generation technology used for RCP can be re-used for final implementation. To a certain extent this is also valid for the code generation required for autotyping the plant models for a HIL simulator. In some cases an RCP platform may actually serve as a simple HIL simulator.

The upper right part of the cycle mentions function optimization, which seems to be separated from the RCP stage, but as the following paragraph describes, this phase is also partly covered by the BHEV RCP Platform development.

### 3. BHEV RCP platform

The BHEV RCP Platform comprises 2 main developments:

- Development of a so called ‘embedded target’ for generating code from MATLAB/Simulink for a Rexroth RC30 series automotive specified controller (ECU). This target originally got the name ‘RC30 Target’ and is now being part of the HANcoder library of embedded targets, ex-tending its full name to ‘HANcoder RC30 Target’;
- Development of an application engineering tool, named HANtune, to serve as a real time dashboard for the algorithm running in the RC30 ECU.

On the left, the Simulink environment is shown with the library browser containing the available functional blocks for building models on the far left. HANcoder RC30 Target adds a library of blocks for connecting a Simulink algorithm to inputs and outputs of an RC30 controller. Additionally, some blocks for system management (e.g. hardware configuration) and memory management are provided.

When the necessary blocks of HANcoder RC30 Target are properly configured and connected to the model, code can be generated from the model fully automatically. The generated code can directly be programmed into the controller, shown in the middle. HANcoder RC30 Target supports different versions of the RC30 family. The differences in hardware versions are twofold:

- The amount of relatively expensive power outputs is varied for unit price reasons;
- More recent hardware versions contain additional safety aspects for supporting safety relevant application development.

In the light of EPT, support for a controller with integrated safety functionality was realized in order to prepare future support for series production developments requiring these aspects. More information on the supported hardware in HANcoder RC30 Target can be found at www.han.nl/rc30target.

The attractive aspect of the RC30 series controllers is the series production quality and service, combined with a significant amount of inputs and outputs providing a wide variety of functionality. This enables RCP and series product development based on the same hardware family, in line with the set targets for the BHEV RCP Platform.

When the generated code is executed in an RC30 controller, a wish for monitoring and optimizing the algorithms’ behaviour emerges. This is enabled by HANtune shown on the right side of the picture. Via the industry standard XCP protocol, HANtune connects to the running algorithm in the RC30 controller. When connected, the user can visualize, log and optimize signals and parameters in real-time. This provides an efficient workflow for RCP activities. The logged data can be transferred back to MATLAB/Simulink® for simulation purposes as well. More information on HANtune can be found at www.han.nl/hantune.

During the EPT project, several students worked together with employees on the continuous development of HANcoder RC30 Target and HANtune, upgrading them to an attractive solution. On the educational side this resulted in combining HANtune with another code generation solution based on a low-cost Freescale HCS12 microcontroller already in use at minor ‘Autotronica’. By combining these tools, students got access to model based development tools resulting in a significant increase of effectiveness in the minor projects. Using these tools, students are able to design, implement and test algorithms with higher complexity in shorter time frames compared to the original process using manual coding.

Students can put more focus on functionality instead of programming language and microcontroller behaviour when using the tools. Besides, true model based development scenarios became reality in our educational environment as described below in the application examples.

### 4. Extending the horizon

In parallel to the educational integration, several parties became interested the HANcoder/HANtune solution as well, resulting in co-development [2] by one of these parties. As a consequence the application horizon extended beyond that of EPT, leading to a proposal for a separate project focusing on tool development in a community environment for RCP purposes: the RAAK-MKB project Fast & Curious [3]. During Fast & Curious, many project partners started adopting the HANcoder/HANtune solution in their development process, specifically for prototyping purposes. The usage was not limited to Fast & Curious partners. Other parties started using the tools as well [4, 5, 7]. During Fast & Curious, several SME partners expressed a wish for integration of RCP and series production developments. Consequently, a new RAAK-MKB project called SMARTcode [6] focusing on model based development for series products started in October 2014.

### 5. Safety handbook

As mentioned in the introduction, in early EPT stage the idea arose to develop a pragmatically oriented handbook for applying the functional safety related procedures and methods as ISO26262 proposes in electric power train control systems. Since ISO26262 is very comprehensive and leaves interpretation and choice of methods open to some extent, a handbook can be of practical assistance, especially for SMEs that do not have the necessary competences and experience available.
ISO26262 covers the whole product lifecycle. The handbook activities in the light of EPT focused mainly on the concept phase. A good handbook uses real life examples, so the RAAK International project PLUTO project served one of the main cases for the handbook. Various bachelor and master students worked on the handbook covering various aspects. Some examples of the activities:

- Development of a good format for the handbook with the appropriate interactivity, including a short explanation of background and content of ISO26262;
- Design of generically usable torque manager for electric power trains using model based development techniques and tools;
- Assessment of the model based verification and validation tools, such as Simulink Design Verifier, being able to automatically generate test cases for a given algorithm model to assess model design errors using formal methods;
- PLUTO control algorithm development was extended with HARA (Hazard Analysis and Risk Assessment) in order to adapt the controller design with respect to functional safety, providing a real life HARA example and good practice input for safe controller design on the model level.

The current status of the handbook is an interactive Word/PDF document describing the largest part of the concept phase as defined by ISO26262, including a flowchart approach assisting in proper process execution, see Figure 3. This handbook will be further extended towards an SME oriented recommended practice in the light of the SMARTcode project.

6. Application examples

HANcoder and HANtune have become the standard tools in control developments within the Automotive and Engineering departments of HAN. Many community members of the projects Fast & Curious and SMARTcode use this toolset in control system developments. Figures 4 and 5 show some example applications that have been developed in a model based way using the tools.

The HyDoblo contains an electric power train combined with a fuel cell system, providing both fuelling options from the grid and from compressed hydrogen. Top level power train control and complete fuel cell system control is handled by a Rexroth RC36-20/30 controller, programmed in Simulink, using HANcoder.

The PLUTO project targets at PLUg-in hybrid power train TOols. Within PLUTO, a plug-in hybrid power train test bed was developed, including all the necessary control systems. PLUTO uses automatically generated code from HANcoder in several ways:

- The PCU (Power train Control Unit) executing high level power train management is implemented in a Rexroth RC28-14/30 controller by the HAN;
- The TCU (Transmission Control Unit), controlling the used twin speed power shift gearbox is implemented in a Rexroth RC28-14/30 controller by Punch Powertrain;
- DC bus safety and control is implemented in a Rexroth RC28-14/30 controller by HAN.

The algorithms in all controllers are defined in MATLAB/Simulink and autocodered in the Rexroth hardware using HANcoder RC30 Target. The resulting software has been tuned using HANtune.
During the control system development in PLUTO plant models have been developed for power train components and vehicle behaviour. These models have been used in various stages of the development, when no real power train hardware was yet available:

- At simulation level for early development of algorithms;
- In HIL simulation to test and optimize real-time behaviour of the control algorithms.

This type of concurrent engineering is one of the powerful aspects of model based development in a real life project, utilized by the PLUTO control team in this way (see Figure 6).

7. Model based development community

The EPT developments of the BHEV RCP Platform induced the projects Fast & Curious and SMART-code, resulting in a community centred around model based development.

The community not only focuses on automotive applications. Extension towards industrial applications has been implemented. Within the community a Change Control Board, existing of commercial partners and HAN, is forcing priorities for further development in order to ensure a ‘market push’ oriented development. The combined industrial and automotive orientation of the community has shown its potential in bilateral exchange of experience and requirements for future developments. One of the interesting results is the realization of the new STM32 Target being usable in both application areas. This target is currently the most used solution in the HANcoder library.

8. Conclusions

The BHEV RCP Platform activities in EPT have fit the need for adequate RCP solutions within the project scope and beyond. Development of the platform as intended was initially executed during phase 1 of the project, resulting in an effective first platform solution. This solution was successfully applied in various projects. Because of a growing interest beyond the scope of EPT, the RCP platform development took a next step in the projects Fast & Curious and SMARTcode, resulting in a community around model based development. By migrating the development into this community environment, the original targets of the BHEV RCP Platform have been surpassed in many aspects. However, for the same reason some original development targets, like the universal safety controller, have not yet been fully realized. The expectation is that the market as represented by the current group of community members will eventually drive the development towards similar solutions if this is really a market wish. That immediately shows the relevance of the new development setting: further, market driven development, automatically optimizing application potential.

References

A prototype emission free cooling trailer

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Abstract

Cooling trailers need a substantial amount of power to drive the cooling compressor. This power is produced by linking the compressor to the engine power take-off or by a reefer unit. An interesting option is to design an autonomous cooling trailer that powers the compressor from brake energy, solar power and from the grid. This paper describes the design and test of such a system, which also comprised a lead acid type battery for storing electric energy. The objective of this study was to design and realize a fully functional prototype trailer and also to design an energy management strategy for this system. The paper presents some preliminary test results, showing its feasibility.

Introduction

Fuel consumption of road going vehicles is an increasing concern for the entire automotive industry. Commercial vehicle manufacturers spend a lot of their efforts in improving the fuel economy of their vehicles, not only to comply with government regulations, but also to preserve the competitiveness of their valued customers. Trailer manufacturers also contribute to this by making their products lighter. Nowadays 10 to 15% of all goods are transported in conditioned trailers. Most conventional cooling systems on trailers, also referred to as reefer systems, are powered by separate diesel engines. An obvious advantage of these systems is the instantaneous availability of ample cooling power, independent of the towing truck. Disadvantages are: high weight, additional engine maintenance, relatively low efficiency and high exhaust and noise emissions. In other systems, the electrically driven compressor is powered via a hydraulic drive from the truck engine power take-off. An overview of the approaches to reduce energy consumption and environmental impacts of refrigerated food transport is given by Tassou et al. [1]. This paper describes the design of a novel system, comprising a regenerative braking module, mounted on one of the trailer axles, a solar panel module, a trailer box and a Li-ion battery for energy buffering. A comparable system, but without the regenerative braking module, was designed and tested by Bahaj et al. in 2000 [2]. A comprehensive feasibility study on solar powered refrigeration for transport application has been reported by Bergeron [3]. This paper concludes that “…the economic justification for wide spread use of solar is moderate, but not compelling. However, as the price of diesel increases and the price of solar modules and vacuum panels decreases, the economic case will improve. These are expected trends. In addition, any new regulations impacting diesel emissions will likely favour solar”.

The main layout of the proposed system and its main characteristics will be presented. The control system will be described, including the energy management system. The system was realized and preliminary test results will be given.

System description

A schematic overview of the system is represented in Figure 1. The subsystems will be described in the following sections:

Solar panels:
The roof of the trailer is covered with about 35 m² PV solar array, generating approximately 4.5kWp power. The array is coupled to an inverter and a battery, which acts as a buffer for storing electrical energy.

Battery:
For first tests a 48 [V], 30 [kWh] lead acid battery was mounted. This battery serves a number of purposes: storing electrical energy from the solar array and regenerative braking and powering the cooling machine.

Regenerative braking axle:
A special axle (see Figure 2) was developed for the prototype trailer, comprising a drive shaft connected to one of the trailer wheels, and a hydraulic pump with variable displacement, which in turn is connected to a hydraulic motor, driving a generator. This solution allows for a continuously variable control of the generator speed, independent of the wheel speed. When the braking light of the trailer is lit, the axle can be used to generate braking power which can be recuperated in the battery, instead of wasted in heat.

Cooling unit:
Cooling power is generated by an electrically driven TRS Alaska cooling unit.

Inverters:
Three Victron Energy 48/10k Quattro inverters were used to convert the battery DC power into 380Vac-50hz. This power can then be used to drive the compressor of the cooling unit. Also the power from the

Figure 1. Schematic overview of the Prototype Emission Free Cooling Trailer

Figure 2. Picture of regenerative braking axle.

1 This paper has been presented at the FISITA world congress, Maastricht, 2014
A regenerative braking axle is connected to these inverters, see also Figure 3. An additional input to the inverters allows for charging of the battery from a mains supply.

Cooling buffer:
The cooling buffer was not used during the tests described in this paper.

The control system
The Rexroth RC28 control unit forms the heart of the control unit (see Figure 3). This industrial controller has a powerful processor, and is completely programmed by Simulink code generation. Monitoring and calibration of the software can be done by using HAN-Tune. Basically the controller has three tasks, communication, energy management and component protection.

Communication
The control unit obtains information from the inverters, the hydraulic system and external sensors. As output it sends the necessary control signals for energy generation and hydraulics. The control unit also takes care of an external CAN logging device, which is able to store desired information on a flash card. Also a display is controlled, which can inform the truck driver about the actual status and errors in the system. Exchange of information between the systems is done via CAN.

Energy management.
The main task of the energy management system is to ensure cooling of the payload. Temperature control is done by the cooling system itself, but the trailer control unit has to make sure there is always energy available for cooling. Multiple energy sources are available and the system has to select the preferred one(s), balancing the availability and price of energy. The energy that is always for free comes from the solar array. So when it is available it is used to charge the batteries, until the desired maximum SOC is reached. Additional power is available from the generator, connected to the regenerative braking axle. Energy from the generator is for free when it is created during deceleration or braking of the trailer, so this is preferred. When still not enough energy is available, for example during a long highway drive during the night, the control system can decide to enable the generator also during constant driving. The truck engine has to produce extra power for this. Because of the high efficiency and low emissions of the truck engine this still is a sensible way of energy generation. When the trailer is connected to the grid this energy is used for both cooling and charging of the batteries.

Component protection.
With the hydraulic transmission from wheel to generator it is possible to run the generator at its required speed down to very low vehicle speeds. This leads to increasing torque in the power take off. To ensure the integrity of all mechanics, the generator is switched off below a certain vehicle speed, and thus above a certain torque limit.

Although with current power levels not a realistic threat, the component protection software has to prevent blocking and thus sliding of the trailers’ wheel, caused by a too large power take off. Comparable to ABS functionality, the controller is monitoring the maximum deceleration of the trailer wheel. At deceleration above a threshold based on the friction between tire and road surface, the generator is switched off.

Operation

![Figure 3. System overview, showing power flow, analogue and CAN-bus signals.]

![Figure 4. Test results for Test 1.](attachment:image)
Several tests have been carried out with prototype cooling trailer and results of two experiments are reported in this section.

### Test 1

Test 1 was done by driving the trailer at a constant speed and was intended to test the functional performance of the regenerative braking axle, mainly. The vehicle was driving 90 [km/hr] most of the time, see Figure 4. The solar array was not operating during this test but the axle was used frequently, as can be seen in Figure 4d. Here it can be seen that the axle (signal AC IN1) during this test produces about 15 [kW] when it is activated. When the cooling unit is running, it consumes about 5 [kW] (signal AC OUT), leaving about 10 [kW] to charge the battery. From Figure 4b it can be concluded that the setpoint temperature is reached at about 1.3 [h]. This causes the subsequent on-off behaviour of the cooling unit, also witnessed in Figure 4d. The Charge demand signal of the battery is set to zero when the battery SOC reaches 80 [%] and is set to 1 when the SOC drops below 70 [%] (see Figure 4e). For this reason the generator stops supplying power at t=1.8 [h] and the battery is used from that time onwards to cool the trailer.

From this measurement it can be seen that the regenerative braking axle alone is quite capable to supply the power needed to cool the trailer and to sustain or increase the battery SOC (Figure 4d).

### Test 2

Test 2 showed frequent stops and two periods of system shutdown, starting at t=0.92 [h] and at 2.05 [h]. During these periods, also the cooling unit was shut down, and the temperature can be seen to rise quickly (see Figure 5b). When the vehicle speed becomes lower than 30 [km/h] the braking axle cannot supply energy to the cooling unit and the required power is obtained from the battery. Figure 6 shows a delay of over 30 [sec] after the trailer reaches 30 [km/h] before the regenerative braking axle starts producing power. This delay is mainly caused by the inverters. Nevertheless, also for this test the axle is able to increase the SOC of the battery, indicating that the power rating of the axle is sufficient for its purpose. The solar array, however, supplies just about 0.8 [kW] on average during Test 2, while the average power consumed by the cooling unit amounts to 4.7 [kW]. Further analysis is required to investigate whether the installation of the solar array pays off under western European climate conditions.

### Discussion

As shown in the sections above, the sizing of the various components (battery capacity, regenerative braking axle power, solar array power) may need further optimization. The system replaces a conventional reefer system, powered by a diesel engine. These systems represent a weight of approximately 750 [kg]. The weight of the proposed system is primarily determined by the battery weight, which amounts also to approximately 500 [kg]. A further reduction in weight may be reached by optimizing battery capacity and by using Lithium based battery technology.

A sophisticated energy management system may further reduce the fuel consumption. An example is the use of a planning system. If the next truck-stop duration will be sufficiently long and a grid connection is available, it may be advantageous to arrive there with a low battery SOC, since energy from the grid comes at lower cost than energy generated by the truck engine.

A system described in this paper comes with additional advantages. The truck driver may use the available energy in the battery for hotel load applications. This may also lead to additional fuel savings and emission reductions, since the truck engine is not needed for this. The required inverter is already present, avoiding extra cost.

### Conclusions

In this paper, a Prototype Emission Free Cooling Trailer was presented. The system design was described, as well as the trailer control system. Experimental test results were presented, showing that the system is feasible from an energy perspective. Further work needs to be done in order to optimize component sizing and the energy management.

### Acknowledgements

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References


Design and test of a battery pack simulator

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Abstract

This paper describes the design of a battery pack simulator (BPS). The BPS is an electronic device that emulates all cell voltages of a battery pack that consists of at most 248 cells in order to test battery management systems (BMS). Cell characteristics and environmental conditions of individual cells, such as capacity, ambient temperature and internal resistance can be adjusted in order to examine the unbalance in a battery pack on the functioning of the BMS. The BPS implements a real time simulation model that consists of interacting electric and thermal submodels. The BPS uses xPC Target and Simulink as real-time software environment. A hardware interface converts all simulated cell voltages and temperatures to real voltages that can be connected to the voltage and temperature sensor inputs of a BMS. We have tested the BPS by comparing the emulated cell voltages of it to the cell voltages of a real battery pack that consists of LiFePO4 cells. In order to do so, a thermal cell model and third order equivalent network model has been derived by analysing EIS1-measurements and pulse current measurements. The found network is implemented in the BPS. Test results show that the maximum deviation between the real and emulated cell voltages is at most 0.5%. We have connected our BPS to a Lithiumate Pro BMS and evaluated the capability to test it with our BPS. We found that basis functionality, like SoC estimation and over and under voltage detection could be tested well. At this moment, the BPS is not suited to test the balancing feature of BMS. Further development of the BPS is needed to enable the testing of this feature of BMS as well2.

1 Electrochemical Impedance Spectroscopy
2 This paper is a revised version of the paper “Design and test of a battery pack simulator”, presented in EVS 27, 2013.
1. Introduction

The testing and evaluation of battery management systems (BMS) is in practice an awkward and time consuming activity. A complete test includes temperature tests, tests of unbalances in battery packs, tests of unknown initial state of charge values, and so on [1]. Also, it is often difficult to test the BMS in a laboratory with the same load and environmental conditions that a battery pack might face in practice. In order to facilitate the testing of BMS we have designed a battery pack simulator (BPS). The BPS is an electronic device that emulates all cell voltages of a battery pack under various adjustable battery conditions. The BPS can be used also for testing voltage management systems of fuel cell stacks. The BPS calculates the voltages and temperatures of all cells in a battery pack that consists of at most 248 cells. The user can define his own battery model, so batteries with different cell chemistries can be emulated. Cell characteristics and environmental conditions of individual cells, such as capacity or ambient temperature can be adjusted in order to test the impact of unbalance in a battery pack on the functioning of the BMS. The BPS implements a real time simulation model that comprises interacting electronic and thermal submodels. A hardware interface converts all simulated cell voltages and temperatures to real voltages that can be connected to the voltage and temperature sensor inputs of a BMS. This paper explains the architecture of the battery simulator, the hardware interface, the modeling of a battery pack that consists of LiFePO4 cells and the basic testing of an Elithion Lithiumate PRO BMS by using our BPS.

2. Architecture of battery pack simulator

The hardware of the BPS consists of four main components (Fig.1): a host PC, an xPC target, a FPGA board and a set of at most 64 isolation amplifiers.

![Figure 1: Block diagram of the battery pack simulator](image1.png)

The Host PC is the interface between the user and the model. The host PC enables the user to start or stop a simulation, watch simulation results and to enter the model input.

The battery model runs on an xPC target and consists of four subsystems (Fig.2):

![Figure 2: Block scheme of the model that runs on the xPC target](image2.png)

1. The subsystem ‘UDP data from host’ handles the model input that is sent from the host to the xPC target. The model input consists of the battery current and adjustable cell parameters and variables. The model in Fig.2 defines 5 adjustable cell parameters, but this can be expanded according to the user’s needs. Port numbers of the UDP packets are used to identify the adjustable variables and parameters in order to support flexible and easy configurable model implementations.
2. The subsystem ‘UDP data to host’ handles the model output that is sent from the xPC to the host. The model output consists of terminal voltages, temperatures and state of charge of all cells.
3. The subsystem ‘Battery pack model’ defines the cell and battery pack model and is discussed in more details later in this paper.
4. The subsystem ‘FGPA board’ provides the model output that is sent to the FPGA board. The model output to the FPGA board holds 512 variables. In the configuration, shown in Fig.1, the output consists of 248 cell voltages, 248 cell temperatures, the battery pack voltage, a current sensor output. Zero value placeholders are used if the battery pack consists of less than 248 cells. All simulated output variables are scaled to 16-bit variables that can be processed by the digital to analog converters (dac’s) in the isolation amplifiers. An offset calibration feature is implemented to correct offset error(s) that may arise in the analog signal processing circuit. Raw datagrams are used for the communication between the xPC and FPGA since it is a fast and rather simple protocol. The FPGA board is the interface between the xPC target and the isolation amplifiers. The FPGA is responsible for receiving and decoding the Raw datagram packets sent by the xPC target. The FPGA decomposes the 512 output variables into 64 sets of 8 variables that are transmitted to isolation amplifiers circuits by 64 SPI busses. All 64 SPI busses share the same clock- and latch signal in order to limit the number of signals and to provide synchronous sampling. Each SPI bus has its own data signal. The SPI busses are connected to isolation amplifiers. Each isolation amplifier circuit provides eight analog voltages that can be configured to represent cell voltages, temperature sensor signals or a combination of both. The isolation amplifiers provide the analog voltages that can be connected to the BMS cell voltage inputs or temperature or current sensor inputs. Its working is discussed in the next section.

3. Isolation amplifier circuit

Fig.3 shows the functional block scheme of the isolation amplifier circuit. The SPI-bus operates at a bit rate of 500 [kbit/s]. The chosen bit rate limits the maximum sample rate to at most 3.9 [kSamples/s] (=500kbits/s / 8 words * 16 bits)).

The SPI signal are galvanic isolated from the FPGA board by optocouplers. The secondary sides of the optocouplers are connected to 8 daisy-chained 12-bit dac’s. The dac’s are grouped in two sets of four isolation amplifiers that share a common power supply. An analog processing circuit converts the voltages of the dac’s to output voltages. The design of the analog circuit allows the following configurations:
- Configuration 1 is applicable to emulate the cell voltages of eight subsequent cells when the BMS under test uses multiple cell monitor units. Then, it applies: \( U_{\text{out}1} = U_{\text{adc}1}, U_{\text{out}2} = U_{\text{adc}2}, U_{\text{out}3} = U_{\text{adc}3} \) and so on. The gnd2 connection of the upper analog processing circuit must be connected to \( U_{\text{out}} \) of the lower analog process circuit.
- Configuration 2 is applicable to emulate the temperature sensor voltages of eight subsequent temperature sensors when the monitor unit of the BMS under test uses analog temperature sensors with a common ground. In that case, it applies: \( U_{\text{out}} = U_{\text{adc}1}, U_{\text{out}2} = U_{\text{adc}2}, U_{\text{out}3} = U_{\text{adc}3} \) and so on.
In this paper we describe the modeling of a battery pack that consists of twelve 100 [Ah] Sinopoly LiFePO4 cells. The 12 cells were placed in one row (see Fig.4.).

### 4.1 Thermal submodel

The thermal model of the battery pack is based on the thermal heat conductance between the cells mutually and from the cells to the environment [2], [3], [4]. We used equation 1 to determine the cell temperatures.

$$T_i = T_i^0 + \frac{1}{C_{th} \cdot \kappa_{cc}} \int \left( P_i + \kappa_{ca} \cdot (T_i - T_o) + \sum_{j=i,j \neq i} \kappa_{ij} \cdot (T_j - T_i) \right) dt$$

where: $T_i^0$ = initial temperature of cell i, $C_{th}$ = heat capacity of cell, $P_i$ = heat dissipation in cell i, $\kappa_{ca}$ = heat conduction coefficient from cell i to ambient, $T_j^0$ = ambient temperature of cell i, $\kappa_{ij}$ = heat conduction coefficient from cell i to cell j.

The heat production of cell i consists of a part that arises from the entropy change of the reaction and a part caused by the overpotential voltage. In our model it is calculated as [5]:

$$P_i = I \cdot (U_{ocv} - U_{t,i})$$

$U_{ocv}$ = open terminal voltage of cell i and $U_{t,i}$ = terminal voltage of cell i.

We did not take the reversible heat effect into account. We measured the heat capacity of a cell by means of a calorimeter and found a value of:

$$C_{heat} = 4090 \ [J/K].$$

This corresponds to a specific heat capacity of 1.3 \ ([J g^{-1} K^{-1}]). This is 15% more than reported by [6].

The heat conduction coefficients have been determined by measuring the stationary temperature rise of all cells when the pack is loaded by an 80 [A] alternating charge / discharge current (see Fig.5).
Because of the symmetry of the current, the average internal power loss in the cell can be calculated as:

\[ P_i = 80 \, [\text{A}] \cdot \frac{1}{T} \int_0^T U_i \cdot \text{sign}(i) \cdot dt \quad (2) \]

where: \( U_i \) = terminal cell voltage of cell \( i \), \( T \) = period time of current.

Table 1 lists the average power losses and temperature rise of each cell.

<table>
<thead>
<tr>
<th>cell nr.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_i ) [W]</td>
<td>4.1</td>
<td>4.3</td>
<td>4.4</td>
<td>4.1</td>
<td>4.5</td>
<td>4.5</td>
</tr>
<tr>
<td>( \Delta T_i ) [°C]</td>
<td>9.4</td>
<td>11.5</td>
<td>12.5</td>
<td>13.2</td>
<td>13.1</td>
<td>13.4</td>
</tr>
</tbody>
</table>

Based on the construction of the battery pack, we assume three independent heat conduction coefficients. These are:

- \( \kappa_{ca} \): the heat conduction coefficient of all cells but cell 1 and 12 to ambient
- \( \kappa_{cc} \): the heat conduction coefficient between two adjacent cells (\( i=j+1 \) or \( i=j-1 \)).
- \( \kappa_{ca} \): the heat conduction coefficient of cell 1 and 12 (the cells on the edge of the pack) to ambient

The heat conduction coefficients of non-adjacent cells are assumed to be 0.

The three heat conduction coefficients \( \kappa_{ca} \), \( \kappa_{cc} \) and \( \kappa_{ij} \) were determined by least squares fitting of the data of table 1 and the equation 3.

\[ P_i = \kappa_{ca} \cdot \Delta T_i + \sum_{j \neq i} \kappa_{cc} \cdot (\Delta T_j - \Delta T_i) \quad (3) \]

We found the following values:

- \( \kappa_{ca} = 0.47 \, [\text{W/K}] \)
- \( \kappa_{cc} = 0.34 \, [\text{W/K}] \)
- \( \kappa_{ij} = 0.06 \, [\text{W/K}] \)

4.2 Electric submodel

In order to determine the electric model, we have executed three kinds of measurements:

1. Open terminal voltage measurements
2. EIS-plot measurements
3. Current pulse measurements

4.2.1 Open terminal voltage measurements

We measured the terminal voltage during a C/50 charge and discharge current at temperatures of \( T=0\,^\circ\text{C} \), \( T=25\,^\circ\text{C} \) and \( T=40\,^\circ\text{C} \). Fig.6 shows the measurement results. The graphs show a clear hysteresis effect that increases at low temperatures. This effect has also been reported in literature [7], [8]. In our model we didn’t include the hysteresis effect. We used the average value of the terminal voltage of the charge and discharge curve as the open circuit voltage as a function of the SoC.

4.2.2 EIS-plot measurements

We measured the cell impedance as a function of the SoC at a temperature of 0 °C, 25 °C and 40°C. The measurements were carried out by means of an NIUUM STAT impedance analyzer in a frequency range of 50 [mHz] to 659 [Hz] while discharging the cell at a current rate of C/10. Fig.7 shows the EIS-plots that are made out of the measurement results. We have limited the frequency range of the EIS-plots from 50 [mHz] to 659 [Hz], because at higher frequencies the self inductance of the cell was getting the dominant impedance and we did not include this in our model.
4.2.3 Current pulse measurement
We have measured the pulse response of 12 cells in series that are loaded by the pulse shaped current profile that is shown in Fig.8. We have measured the pulse response for charge and discharge current pulses. The measurement has been performed at room temperature (22 °C).

![Figure 8](image)

Figure 8 left: Current and voltage of cell 1 during a discharge pulse current profile. Each pulse lasts 600 [s] and is followed by a 600 [s] rest period. Figure right: Current and voltage of cell 1 during a charge pulse current profile. Each pulse lasts 600 [s] and is followed by a 600 [s] rest period.

4.2.4 Battery model
The base of our battery model is the practical circuit-based model proposed in [9]. This model reduces a typical Randell circuit that applies for LiFePO4 cells to a second order impedance circuit. We adapted this circuit to a third order circuit as shown in Fig.9. In Fig.9, Rb represents the bulk resistance, the parallel circuit of Rs and Cs models the activation polarization and the parallel circuits of Rlb//Clb and Rla//Cla model the concentration polarization.

![Figure 9](image)

Figure 9: Third order impedance circuit that is applied in our battery pack simulator.

We determined the values of Cs and Rs from the half circles of the EIS-plots. The EIS-plots of Fig.7 show that Cs and Rs have a hardly noticeable dependency on the SoC. Therefore, we neglected this dependency in our model. However, the EIS-plots of Fig.7 do show a dependency on the temperature. Table 2 shows the values of Cs and Rs that we found via curve fitting of the EIS-plots.

Table 2: Values of Rs, Cs and τs at three temperatures. The time constant τs is calculated as: \( \tau_s = R_s \cdot C_s \)

<table>
<thead>
<tr>
<th>T (°C)</th>
<th>Rs [mΩ]</th>
<th>Cs [F]</th>
<th>τs [ms]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.4</td>
<td>6.4</td>
<td>9.0</td>
</tr>
<tr>
<td>25</td>
<td>0.24</td>
<td>21</td>
<td>5.0</td>
</tr>
<tr>
<td>40</td>
<td>0.04</td>
<td>88</td>
<td>3.5</td>
</tr>
</tbody>
</table>

We have investigated the dependency of \( R_s \), \( C_s \) on charging and discharging at room temperature. We did not measure a clear dependency. Therefore, we assumed that the values above apply for both charging and discharging.

The values of \( R_{lb}, R_{la}, C_{lb} \) and \( C_{la} \) were determined from the pulse current measurements [10]. The sample time of the pulse current measurements was 0.1 [s]. This is more than 10 times higher than the time constant of the \( R_s/C_s \) circuit, so the transient behavior of the measured pulse response is determined by the \( R_{lb}/C_{lb} \) and \( R_{la}/C_{la} \) circuits.

By curve fitting of the cell voltage during the rest period intervals to equation 4, we found the values as a function of the state of charge.

\[
U_{cell}(t) = U_b + I_{pulse} \cdot \left( R_s \cdot \frac{e^{\frac{t}{\tau_s}} - 1}{e^{\frac{t}{\tau_s}} + 1} + R_l \cdot \frac{e^{\frac{t}{\tau_l}} - 1}{e^{\frac{t}{\tau_l}} + 1} \right) \tag{4}
\]

Where: \( U_{cell}(t) = \) cell voltage as function of time, \( U_b = \) stationary voltage, \( I_{pulse} = \) magnitude of current pulse (-50 [A] for discharge pulses and 50 [A] for charge pulses), \( U_b = R_s/C_s \cdot \) time constant of the \( R_s/C_s \) circuit, \( \tau_b = R_l/C_l \cdot \) time constant of the \( R_l/C_l \) circuit.

We didn’t measure the temperature dependency of \( R_{lb}, R_{la}, C_{lb} \) and \( C_{la} \). Instead, we assumed that the temperature dependency of the concentration polarization of our cells is the same as is measured in [9] for LiFePO4 cells. We used the empirical relations described in [9] and scaled them as follows:

Charging: \[ R_{lb}(soc,T) = \frac{R_{lb}(soc,22°C)}{R_{lb}(soc,22°C)} \cdot R_{lb}(soc,T) \]

Discharging: \[ R_{lb}(soc,T) = \frac{R_{lb}(soc,22°C)}{R_{lb}(soc,22°C)} \cdot R_{lb}(soc,T) \]

\[ C_{lb}(soc,T) = \frac{C_{lb}(soc,22°C)}{C_{lb}(soc,22°C)} \cdot C_{lb}(soc,T) \]

\[ C_{lb}(soc,T) = \frac{C_{lb}(soc,22°C)}{C_{lb}(soc,22°C)} \cdot C_{lb}(soc,T) \]

Where: \( R_{lb}(soc,T), R_{la}(soc,T), C_{lb}(soc,T) \) and \( C_{la}(soc,T) \) are the circuit parameter equations given in [9]. In the equations above, the subscript c is used for charging and d for discharging.
Where: $\Delta U$ and $\Delta I$ are the voltage and current change, measured at the end of the pulse and start of the rest period.

At $T=22$ [°C] we found 0.8 [mΩ] for the sum of $R_b$ and $R_s$. For the bulk-resistance we then find:

$$R_b = 0.5 \text{ [mΩ]}$$

The value of $R_b$ found above is about 0.6 [mΩ] less than the value that can be derived from the EIS-curves. This difference is caused by the contact resistance of the connections to the IVIUM STAT impedance analyzer that is used to measure the EIS-curves. This difference is caused by the contact resistance of the connections to the IVIUM STAT impedancer that is used to measure the EIS-curves. The bulk resistor $R_b$ is determined from the pulse current measurements. Because the sample time is much larger than the time constant of the $R_s/C_s$ and much smaller than the time constants of the $R_a/C_a$ and $R_d/C_d$ circuits, it applies:

$$R_b + R_s = \frac{\Delta U}{\Delta t}$$

Where: $\Delta U$ and $\Delta I$ are the voltage and current change, measured at the end of the pulse and start of the rest period.

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Finally, the SoC in our model is calculated by:

$$SoC = SOC_i - \frac{\int I_i \, dt}{C_i}$$

Where: $SOC_i$ is the initial state of charge of cell $i$ and $C_i$ is the capacity of cell $i$.  

Fig.10 shows the values of $R_{la}$, $R_{lb}$, $C_{la}$ and $C_{lb}$ for charging and discharging.

The bulk resistor $R_b$ is determined from the pulse current measurements. Because the sample time is much larger than the time constant of the $R_s/C_s$ and much smaller than the time constants of the $R_a/C_a$ and $R_d/C_d$ circuits, it applies:

$$R_b + R_s = \frac{\Delta U}{\Delta t}$$

Where: $\Delta U$ and $\Delta I$ are the voltage and current change, measured at the end of the pulse and start of the rest period.

At $T=22$ [°C] we found 0.8 [mΩ] for the sum of $R_b$ and $R_s$. For the bulk-resistance we then find:

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### 5. Model validation

In this section we discuss the model validation. We do this by comparing the cell voltages and temperatures of the battery pack shown in Fig.4 to the simulated results of a model of the same pack. As the validation current profile, we used the measured current of the motor controller of an electric Fiat Doblo while driving the low power NEDC [11]. We have loaded the battery pack twice with the measured current. We introduced a 300 [s] rest period at the end of the first and second current profile, Fig.11 shows the validation current. The validation current varies between -203 [A] and 367 [A] and has a standard deviation of 94 [A]. The sample time of the validation measurement is 0.1 [s].

![Figure 11: Validation current profile](image)

The measurement started with a fully charged battery pack at 21 [°C]. At the end of the measurement, the SoC was reduced to 49%.

Fig.12 left shows the averaged measured and simulated cell voltage as a function of the time. We averaged the cell voltages of all cells. Fig.12 right shows the difference of the averaged measured and simulated cell voltages.

![Figure 12: Simulated and measured cell voltage](image)

The measurement started with a fully charged battery pack at 21 [°C]. At the end of the measurement, the SoC was reduced to 49%.

Fig.12 left shows the averaged measured and simulated cell voltage as a function of the time. We averaged the cell voltages of all cells. Fig.12 right shows the difference of the averaged measured and simulated cell voltages.

![Figure 12: Simulated and measured cell voltage](image)

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Fig.12 left shows the averaged measured and simulated cell voltage as a function of the time. We averaged the cell voltages of all cells. Fig.12 right shows the difference of the averaged measured and simulated cell voltages.

![Figure 12: Simulated and measured cell voltage](image)
The absolute difference of the simulated and measured voltages is in the entire time range below the 50 [mV]. The standard deviation of the difference of simulated and measured voltage is 14 [mV]. This can be translated to a difference in the overall resistance of 0.15 [mΩ], which is about 10% of the sum of all resistances in the model.

Fig. 13 shows the measured and simulated temperature of one cell at the edge of the pack and a cell in the middle of the pack. Also, the measured ambient temperature is shown.

Fig. 13 shows that the difference between the simulated and measured temperatures gradually increases to about 2 [°C] at the end of the test. This difference can be explained by the raise of the ambient temperature during the measurement, while the ambient temperature in the model has been constant. We also observe more high frequency components in the response of the measurements. We explain this by the heat dissipation at the poles caused by the contact resistance. The temperature sensors are mounted on the poles of the cells, so the measured temperatures are relatively strongly influenced by the local heat dissipation on and around the poles. In the model, the poles and connection strips are part of the heat capacity of the cell. No temperature gradients exist in the cell model which results in a flatter temperature graph.

6. Battery pack simulator tests

In order to evaluate the BPS, we have connected it to an Elithion Lithiumate Pro BMS. The BPS was loaded with the twelve cells battery pack model that is discussed in the previous sections. We tested the following features:
- The accuracy of the emulated cell voltages of the BPS compared to the model output.
- The transient behaviour of the emulated voltages.
- The SoC estimation of the BMS when it is connected to the BPS.
- The correct working of the under and over voltage detection of the BMS.
- The maximum sample rate of the BPS

As explained before, we cannot test the balancing functionality of the BMS because of the limited output current of the isolation amplifiers. Also, we did not connect the temperature sensors of the cell monitoring units of the BMS to our BPS, so the temperature related functionality of the BMS is not tested.

6.1 Accuracy of emulated voltages

The accuracy of the emulated voltages of the BPS is determined by comparing the measured emulated cell voltages to the model output. We use the current profile shown in Fig. 11 for this test. The sample time of the test is 0.1 [s]. Fig. 14 shows the emulated and simulated cell voltage of cell 1. The measured and simulated cell voltages of the other cells are comparable. The difference between both signals becomes only visible when zoomed in to a small area of the graph.

![Figure 14: Emulated and simulated voltage of cell 1 when the battery pack is loaded with the validation current profile of Fig. 11.](image)

The standard deviation of the difference of the emulated and simulated signal is 1.1 [mV]. This corresponds to the resolution of the digital to analog converter that is used in the isolation amplifier circuit.

6.2 Transient behaviour of emulated voltages

We determined the transient behaviour of the isolation amplifiers by measuring the rise and fall time on a step response. For this test, we emulated a current sensor with a sensitivity of 100 [A/V]. We examined the current sensor output voltage on an oscilloscope when a block shaped current is simulated that alternates between -200 [A] and +200 [A] at a frequency of 10 [Hz]. Fig. 15 shows the rising and falling edge of the emulated current sensor voltage.

![Figure 15: step response of the isolation amplifier on the rising edge (left scope image) and falling edge (right scope image) of a block shaped pulse. The time scale of the scope images is 1 [µs/div].](image)

Fig. 15 shows a rise time of about 3 [µs] and a fall time of 2 [µs]. This is much less than the minimum simulation time of 254 [µs] that originates from the limitations of the SPI bus. This means that the transient behaviour of the hardware hardly plays any role in the dynamic behaviour of the whole system.
6.3 Evaluation of SoC determination
We evaluated the SoC determination of BMS by simulating the battery pack when it is loaded by a current profile that consists of twice the validation current profile shown in Fig.11. Figure 16 shows the SoC, simulated by the BPS, and the SoC estimation of the BMS as a function of the time.

![Figure 16: SoC estimation of the BMS and the SoC calculated by the model.](image)

The difference between the SoC estimation of the BMS and the SoC calculation of the model is less than 0.5%. This corresponds to the resolution of the SoC estimation of the BMS, which is 1%

We also tested the response of the SoC estimation by the BMS on a stepwise change of the SoC of the BPS from 10% to 90%. We saw that the SoC of the BMS estimation did not change. Instead, we saw that the state of health (SoH) was adapted by this change. We also entered a stepwise change of the SoC when the BMS was switched off. Again, the BMS did not report a change in the SoC estimation after turning it on again.

It seemed to us that the SoC estimation was only readapted to 100% after the maximum cell voltage was reached while charging the battery.

6.4 Under and overvoltage detection
Under and overvoltage detection is tested by changing the SoC of the BPS abruptly so that the cell voltages exceeded the under and overvoltage limits. We found that the BMS detected the exceeding of the limits correctly.

6.5 Maximum sample rate
The data transfer on the SPI bus sets the upper limit of the sample rate to 3.9 [kSamples/s]. This limit however may be decreased by the execution time of the model. The execution time depends heavily on the speed performance of the xPC target, the complexity of the model and the number of cells of the battery pack. Table 3 lists the execution time of the model that is described in this paper as a function of the number of cells. We have used a common PC with pentium 4 3.00 GHZ processor and 4 GByte RAM as xPC target.

Table 3: Execution time of the model as a function of the number of cells.

<table>
<thead>
<tr>
<th>number of cells</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>6</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>execution time [µs]</td>
<td>13.9</td>
<td>16.1</td>
<td>17.5</td>
<td>21.6</td>
<td>30.2</td>
</tr>
<tr>
<td>number of cells</td>
<td>24</td>
<td>48</td>
<td>60</td>
<td>120</td>
<td>248</td>
</tr>
<tr>
<td>execution time [µs]</td>
<td>48</td>
<td>84</td>
<td>103</td>
<td>207</td>
<td>477</td>
</tr>
</tbody>
</table>

For our model and xPC target, it applies that the maximum sample rate decreases below 3.9 [kSample/s] when the number of cells is more than 140.

For most battery management systems, this sample rate is sufficiently high and there is enough space to implement more complex models that take more calculation time.

7. Conclusions and further study
The BPS, proposed in this abstract, provides a flexible architecture that can be used to emulate cell voltages and temperatures of a battery pack. We evaluated the BPS by implementing a LiFePO4 battery pack. Test results show that relatively complex models can be simulated at high sample-rates with an acceptable accuracy.

We connected a Lithiumate Pro BMS to our BPS. We found that the basic functionality of this BMS could be tested well with our BPS.

A major shortcoming of the BPS now is the lacking of the capability to test the balancing feature of BMS. Further work will focus on the implementation of this.

Acknowledgments
We wish to thank Strukton Embedded Solutions b.v. for putting an Elithion Lithiumate Pro BMS at our disposal.

This work is supported by Raak PRO EPT.

References
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The modelling of the temperature at the poles and core of large prismatic LiFePO4 cells

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Abstract

The safety and performance of Lithium batteries depend heavily on the cell temperature. Because of this, battery management systems measure the temperature of the cells. When prismatic cells are used, the temperature is often measured at the poles of the cell. This paper investigates the relation between the temperature of the cell core and temperature at the poles of a single cell. A one dimensional model is used to model the core of the cell. The poles are modeled as two heat capacities that are connected to the core by thermal resistances. The model takes into account the heat dissipation because of over-voltage losses, the electric contact resistances between cables and poles and between poles and the core of the cell and the influence of the cables that connect the battery to an external source or load. We validated the model by comparing the measured and simulated temperatures at a load current that gives a more or less constant power dissipation and a load current that causes a block shaped power dissipation. The validation measurements show that the model has an average error of about 5% in steady state simulations. Both model and validation measurements show that the temperature rise at the positive pole is about 15% higher than the rise at the negative pole. The model shows that the temperature rise of the cell core is about the same as the temperature rise of the negative pole.

We used our model to estimate the temperature at the poles and cores of a battery that consists of four cells that has no forced cooling. Simulations show that the difference between the temperature rise measured at the poles and core is less than 5% in a steady state. For a current profile that has relative many transients in it, the difference increases.

1. Introduction

The temperature is a very important quantity when it comes to the performance of a battery. When the temperature of a cell is too high, the aging of the cell accelerates and dangerous situations may occur when the cell temperature is out of the safety operating zone. Also, the temperature is an important factor in estimating the state of charge of a battery. Because of this, the temperatures of cells are measured by a battery management system. When prismatic cells are used, the cell temperature is often measured on or nearby the poles of the cell. This study investigates the difference of the temperature measured at the poles and the average temperature inside a cell.

In the first part of this paper, we describe the modeling of a battery that consists of one cell. For this study we used a Sinopoly lithium iron phosphate cell of 100 [Ah]. We dismounted a cell and derived a thermal model based on the physical construction of the cell. We measured all model parameters by relatively simple experiments that we carried out on a dismounted cell. We added a first order model of the cable that connects the cell to an external load because we don’t want to exclude the influence of the cable on the temperature on the poles.

In the second part of this paper we use the model to estimate the temperature at the poles and inside the cells of a battery that consist of 4 cells in a row.

2. Cell assembly

In order to fully understand the thermal behavior of a cell, we opened a cell to see what is inside. We found that the cell core exists of 112 copper current collectors, holding the Lithium carbon material and the same amount of aluminum current collectors holding the LiFePO4. The sheets are located in between the harmonica-wise folded separator emerged in a liquid PF6 electrolyte. The battery case is 5 mm thick polypropylene. Figure 2 shows the construction of a prismatic battery cell. Table 1 shows some of the characteristics of the cell that are being used in our cell model.

![Figure 2: The upper figure shows in a schematic way the construction of the cell core. The pictures below show the interior of the Sinopoly cell we have investigated.](image)

<table>
<thead>
<tr>
<th>Table 1. Characteristics of cell under study</th>
</tr>
</thead>
<tbody>
<tr>
<td>total mass cell [kg]</td>
</tr>
<tr>
<td>mass aluminum pole[1] [kg]</td>
</tr>
<tr>
<td>mass copper pole[1] [kg]</td>
</tr>
<tr>
<td>mass and dimensions of case [kg]</td>
</tr>
</tbody>
</table>

[1] The mass includes the weight of the nut that is used to fix the pole to the case.
The poles consist of a solid copper or aluminum block on which a cylindrical top is attached. The cylindrical top holds a tapped hole used for bolts to connect a current cable or connector to it. The thread on the outside is used to fix the poles to the case. The copper and aluminum tabs on the current collector foils are squeezed up against both sides of the poles by means of two bars. The construction of the cell implies two electric contact resistances (ECR) at each pole. The first one is the ECR from cable or connector to the pole; the other is the ECR from pole to current collector foils. The contact resistance is an important phenomenon to explain the difference in temperature at the poles and core. Literature [1] shows that ECR may cause a significant contribution of about 7% to the power losses of a cell.

3. Thermal model

Thermal cell modeling can be done in different ways. One of the most complete and accurate models nowadays are the three-dimensional models that couple the electrochemical and thermal behavior and use finite element methods to obtain the three-dimensional temperature distribution inside a cell ([2], [3], [4]). This study, however, is basically mentioned to determine the difference in temperature measured at the poles and the average cell temperature. Therefore, we have chosen to use a relatively simple 1-D cell model. Figure 3 shows the thermal RC-network representation of the model.

The cell model consists of three heat capacities: one heat capacity represents the core of the cell (the inner part of the cell and case); the other two heat capacities represent the two poles. The core and poles are thermally connected to each other by heat resistances. All heat capacities are connected to the ambient by combined heat conduction and heat convection resistances.

We added three heat sources in the model. Heat source \( q_c \) represents the heat that is generated in the core when a current is running because of the overvoltage and the reaction entropy changes. The heat \( q_c \) is generated at the core of the cell. We added two heat sources \( q_{ap} \) and \( q_{cp} \) at the copper and aluminum poles, respectively. These heat sources are generated at the contacts between the poles and the core.

\[
\begin{align*}
q_c &= \text{heat generated in the core} \\
n_q &= \text{heat generated in the aluminum pole} \\
n_{cp} &= \text{heat generated in the copper pole}
\end{align*}
\]

The following network components are being defined:

\[
\begin{align*}
C_c &= \text{heat capacity of the core} \\
C_{ap} &= \text{heat capacity of the aluminum pole} \\
C_{cp} &= \text{heat capacity of the copper pole} \\
R_{ca} &= \text{thermal resistance from core to ambient} \\
R_{qa} &= \text{thermal resistance from aluminum pole to core} \\
R_{pa} &= \text{thermal resistance from copper pole to core} \\
R_{cap} &= \text{thermal resistance from aluminum pole to copper pole} \\
R_{cpa} &= \text{thermal resistance from copper pole to aluminum pole} \\

R_{cell→ambient} &= \tau / C_{cell}
\end{align*}
\]

4. Determination of model parameters

This section describes the determination of the model parameters of the model shown in figure 3.


The heat capacity of the aluminum and copper pole is determined from their mass and the specific heat capacity of aluminum (903 [J kg\(^{-1}\) K\(^{-1}\)], [4]) and copper (385 [J kg\(^{-1}\) K\(^{-1}\)], [4]). We find:

\[
C_{ap} = 37.5 \text{ [J K}^{-1}\] and \( C_{cp} = 50.9 \text{ [J K}^{-1}\]
\]

The heat capacity of the core is determined by measuring the heat capacity of the whole cell, including the poles, by placing it in a calorimeter. We found a value of: \( C_{cell} = 3.05 \text{ [kJ K}^{-1}\] which is in fair agreement with values found in literature [5]. The heat capacity of the core is then calculated as:

\[
C_c = C_{cell} - C_{ap} - C_{cp} = 2.96 \text{ [J K}^{-1}\]
\]

4.2 Heat resistances to ambient.

To determine the heat resistance of the cell to ambient, we heated up a cell to about 40 °C and let it cool down in our laboratory. The time constant, with which the temperature cools down, is found to be: \( \tau = 4.3 \text{ [ks]} \). This gives an overall heat resistance from cell to ambient of:

\[
R_{cell→ambient} = \tau / C_{cell} = 1.42 \text{ [K W}^{-1}\]
\]

The thermal resistance from poles to cell are calculated by the inverse of the product of surface area of the poles (13 [cm\(^2\)]) with the air and the heat convection coefficient of air to a horizontal surface (4 [W K\(^{-1}\) m\(^{-2}\)], [6]). We find:

\[
R_{pa} = 188 \text{ [K W}^{-1}\]
\]

The thermal resistance of core to ambient is then calculated as:

\[
R_c = (R_{cell→ambient} - 2 \cdot R_{pa})^{-1} = 1.44 \text{ [K W}^{-1}\]
\]

4.3 Heat resistances from core to pole.

The heat resistance from core to pole is determined by measuring the temperature difference between pole and core at a known heat flow injected into the pole.

Figure 4 shows the measurement setup that is used. We placed two aluminum spacers between the poles and a steel bar that is heated by an electric resistance wire wrapped around it. To reduce the heat convection around the spacers, we wrapped some tissue paper around them. In the spacer, we drilled two small holes at a distance of 20 mm from each other where we measured the temperature with a K-type thermocouple. The lower temperature hole is located 4mm above the contact area with the pole. We also measured the temperature at the tabs on the aluminum and copper current collector foils inside the battery. To do this, we drilled two holes in the case of the cell.
From this measurement we calculated the thermal core to pole resistance as:

$$R_{\text{core} \rightarrow \text{pole}} = \frac{(T_{\text{pole}} - T_3)}{(q_{\text{spacer}} + q_{\text{bolt}})}$$

where:
- \( q_{\text{spacer}} \) = heat flow through spacer = \((T_1 - T_2) \times k_{\text{aluminum}} \times A_{\text{spacer}} / 20\text{mm} - 1\)
- \( q_{\text{bolt}} \) = heat flow through bolt = \((T_1 - T_2) \times k_{\text{steel}} \times A_{\text{bolt}} / 20\text{mm} - 1\)
- \( T_1 \) = measured temperature on upper part of spacer
- \( T_2 \) = measured temperature on upper part of spacer
- \( T_3 \) = measured temperature on the tabs of the current collectors in the cell
- \( k_{\text{aluminum}} \) = heat conductance of aluminum [205 W m\(^{-1}\) K\(^{-1}\)],
- \( A_{\text{spacer}} \) = cross section of spacer
- \( k_{\text{steel}} \) = heat conductance of steel bolt [17 W m\(^{-1}\) K\(^{-1}\)],
- \( A_{\text{bolt}} \) = cross section of bolt

The temperature on top of the pole (\( T_{\text{pole}} \)) is determined via linear extrapolation:

$$T_{\text{pole}} = T_2 - 4\text{mm} / 20\text{mm} \times (T_1 - T_2)$$

From the measurements and the formulas above, we find the following values for the thermal core to pole resistances:

$$R_{\text{cc}} = 1.7\text{[K W}^{-1}\text{]} \quad \text{and} \quad R_{\text{cap}} = 2.2\text{[K W}^{-1}\text{]}$$

4.4 Electric resistance cable to current collector tabs

We determined the electric resistance by measuring the difference between the voltage on the tabs on the current collectors and the ring on the cable that connects the cable to the pole as a function of the load current. In this way, the measured resistance includes the ECR between cable and pole and the ECR from pole to tabs. The voltage on the tabs is measured by placing two test probes into two holes we made in the case above the tabs positions (see figure 5).

We measured the following values:
- Electric resistance cable to copper current collector tabs = 21 [μΩ]
- Electric resistance cable to aluminum current collector tabs = 87[μΩ]

The measured resistance from cable to aluminum tabs is 4 times higher than that of cable to copper tabs. This is remarkable since the specific resistance of aluminum is only 50% higher than that of copper. The relatively high resistance of the aluminum tabs to cable might be explained because of the higher ECR of aluminum, but we did not investigate this further in this research.

4.5 Thermal model of the cable

The cable, that connects the cell to a source or load, contributes in different ways to the thermal behavior of the cell. On the one hand, the cable is an extra heat conductor through which heat from the pole can flow to the environment. On the other hand, the ohmic heat dissipated in the cable may heat up the pole and cell. Also, the cable forms an extra heat capacitance that affects the dynamic temperature behaviour at the poles.

Figure 6 shows the simple first order thermal model we have used to take into account the influence of the cable. The derivation of this model is given in Appendix A. Table 2 shows the parameter values of the copper cable used in our experiments. The conductor of the cable has a cross-section of 50mm\(^2\).
Table 2: Parameter values of cable model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_{w}$</td>
<td>0.52</td>
</tr>
<tr>
<td>$k_{c}$</td>
<td>401</td>
</tr>
<tr>
<td>$c$</td>
<td>170</td>
</tr>
<tr>
<td>$\rho_{el}$</td>
<td>1.8 $\times 10^{-8}$</td>
</tr>
<tr>
<td>$R_{e}$</td>
<td>7.1 $\times 10^{-3}$</td>
</tr>
<tr>
<td>$R_{k}$</td>
<td>9.8</td>
</tr>
<tr>
<td>$c_{p}$</td>
<td>19.3</td>
</tr>
<tr>
<td>$T_{e}$</td>
<td>188</td>
</tr>
</tbody>
</table>

5. Model validation

Model validation measurements have been carried out by a current profile that exists of symmetrical discharge/charge cycles. A symmetrical discharge/charge cycle is a discharge pulse followed by a charge pulse with the same amplitude and pulse width. The usage of symmetrical discharge/charge cycles makes it possible to determine relatively easily the power dissipation in the cell without needing a complex electric equivalent network model of the cell. Because each discharge/charge cycle is symmetrical, there is no net electrochemical conversion of energy, so all electrical energy input of the battery is converted into heat and can be calculated from the measured voltage and current. For one discharge/charge cycle, the following applies:

$$W_{cycle} = \int_{t_{charge}}^{t_{discharge}} U_{c} \cdot I_{c} \cdot dt$$

$$P_{cycle} = \frac{W_{cycle}}{T_{cycle}} = \frac{\int_{t_{charge}}^{t_{discharge}} U_{c} \cdot I_{c} \cdot dt}{T_{cycle}} = (U_{charge} - U_{discharge}) \cdot I_{abs}$$

Where:

- $I_{abs}$ is the (absolute) value of the current during the charge/discharge cycle
- $T_{cycle}$ is the time span of charge pulse and discharge pulse
- $P_{charge}$ is the average power dissipation during one discharge/charge cycle
- $U_{charge}$ is the average cell voltage during a charge pulse
- $U_{discharge}$ is the average cell voltage during discharge pulse

In total we performed three validation measurements. Figure 7 shows the currents and measured heat dissipation of the validation measurements. In the first measurement, the load current is a continuous series of discharge/charge cycles with a constant amplitude of 125 [A] and pulse width of 20 [s]. The average power dissipation during this measurement varies a little because of the gradual temperature rise of the cell during the measurement and the temperature dependency of the overvoltage ([7], [8]). The first measurement is basically meant to validate the step-response of the model. During the second measurement, the load current is a periodic signal that consists of 3 subsequent charge/discharge cycles followed by a rest period where the current is 0 [A] during 120 [s]. All discharge and charge pulses have an amplitude of 200 [A] and pulse width of 20 [s]. This measurement is meant to validate the thermal behavior at a block wave power dissipation input with a period time of 240 [s].

The third measurement is the same as the second one, only we changed the pulse length to 80 [s] and the amplitude to 150 [A]. This measurement is meant to validate the thermal behavior at a block wave power dissipation input with a period time of 960 [s].

Figure 7: The load current of the cell and the power dissipation calculated according to formula 1 of the three validation measurements. The upper-left graph shows a symmetrical block shaped current that alternately is 120 [A] and -120 [A].

Figure 8 shows the measured and simulated temperatures on the poles and ambient of the three validation measurements. The simulated temperature of the core of the cell is also shown, as well as the ambient and the temperature measured on the case of the cell.

From the graphs of figure 8 we conclude that the model describes the general behavior of the cell well. Both simulations and measurements show that the average temperature rise at the copper pole is smaller than that of the aluminum pole. Also, both simulations and measurements show that the peak-peak value of the temperature response of the aluminum pole on the block shaped power dissipation input at measurement 2 and 3 is much higher than that of the copper pole.

Table 3 shows the measured and simulated temperatures at the poles at the end of the measurement (in the steady state). This table shows that the steady state difference is on average about 5%. The relative difference between the measured and simulated top-top value is higher and more unsteady.
6. Core and temperature at the poles of a battery pack

We used our model to estimate the core temperature and temperature at the poles for a battery that consists of 4 cells placed in row when it is loaded by the current profile that is used in validation measurement 1 and 3. We assumed that the cells are places in open air so the thermal resistance from cell cores to ambient is comparable to the one we found of a single cell. The cells are mutually connected by copper connectors with a length of 80 [mm] and cross-section of 100 [mm$^2$]. Figure 9 shows the battery pack model. The pack model consists of 4 cell models, three connector models and two cable models. The cell model and cable model are shown in figure 3 and 6 respectively.

The connector is modeled by two heat resistances $0.5 \cdot R_{cc}$ that is measured from validation measurement 1 and 3. We assumed that the cells are places in open air so the thermal resistance from cell cores to ambient is comparable to the one we found of a single cell. The cells are mutually connected by copper connectors with a length of 80 [mm] and cross-section of 100 [mm$^2$].

We neglected the ohmic heat dissipation in the connectors.

Also, we added thermal resistances between the cores of adjacent cells and adapted the thermal resistance from core to ambient because the contact area with ambient differs from that of a single cell. In our battery pack model, we made the following assumptions:

- The power dissipation of each cell depends on the temperature of the cell core. We use the dependency that is measured from validation measurement 1 and 3.
- The heat resistance from core to core ($R_{cc}$) is determined by the thermal properties of the case and is calculated as:
  \[ R_{cc} = \frac{2 \cdot \delta_{case} \cdot k_{polypropylene}}{A_{case}} = 6.1 \text{[KW}^{-1}] \]
  where $\delta_{case}$ = thickness of the case (5.5 [mm]), $k_{polypropylene}$ = conductance of polypropylene (0.15 [KW m$^{-1}$ K$^{-1}$]) and $A_{case}$ = contact area of two adjacent cases (≈305 [cm$^2$])
- The heat resistance from core to ambient is inverse proportional to the contact area of the cell with the ambient. A single cell has a contact area of 873 [cm$^2$] and a core to ambient resistance of 1.44 [KW$^{-1}$]. We then find for the corner cells: contact area = 568 [cm$^2$] → $R_{ca1} = 2.2$ [KW$^{-1}$].

We assumed that the thermal resistance from core to ambient is inverse proportional to the contact area of the cell with the ambient. A single cell has a contact area of 873 [cm$^2$] and a core to ambient resistance of 1.44 [KW$^{-1}$]. We then find for the corner cells: contact area = 568 [cm$^2$] → $R_{ca1} = 2.2$ [KW$^{-1}$].
For non-corner cells, we find: contact area = 262 [cm$^2$] $\rightarrow$ $R_{ca2} = 4.2$ [K/W$^{-1}$].

- The heat resistance of a connector that connects the positive pole of a pole to the negative pole of the adjacent cell equals: $R_{con} = \frac{d_{poles}}{k_{copper} \cdot A_{connector}} = 1.0$ [K/W$^{-1}$], where $d_{poles}$ = distance between the poles (61 [mm]), $k_{copper}$ = conductance of copper (401 [W/Km$^{-1}$]) and $A_{connector}$ = cross section of connectors (=150 [mm$^2$]). The heat capacitance of a connector is calculated as the mass of the connector multiplied by the specific heat capacity and equals 31 [J/K].

Figure 9: Model of the battery pack. The red colored symbols are new or changed compared to the model discussed in chapter 3 and 4.

Figure 11 and 12 show the simulated temperatures at the poles and of the core when the battery is loaded with the current profile of validation measurement 1 and 3 (see figure 7).

Figure 11: Simulated temperatures of the poles and core of the 4 cells when it is loaded by the current used in validation measurement 1.

Figure 12: Simulated temperatures of the poles and core of the 4 cells when it is loaded by the current used in validation measurement 3.
7. Conclusions
Most BMS measure the temperature at the poles. This study investigated the relation between the temperature at the poles and that of the cells. A model is made that takes among others into account the heat dissipation at the poles, the heat resistance between poles and core and the influence of the cables that connect a battery to an external load or source. We found that the difference between the pole temperature and core temperature in steady state condition is relatively low when the cell is loaded by a current profile that gives a more or less constant power dissipation in the cell. Only at the corner cells the difference exceeds the 5%. When the cell is loaded by a current profile that contains more transients, the difference increases.

Appendix A Calculation model of cable
Assume a cable with infinite length that is thermally connected to a thermal mass at position x=0. The cable carries a current I that causes an ohmic heat dissipation. The temperature difference with the ambient at x=0 equals $\Delta T_0$. The heat exchange from cable to the thermal mass at x=0 equals $q_0$. Figure A1 shows a part of the cable.

According to the law of conservation of power, it applies for each infinitely small part dx of the cable:

$$c\frac{dx}{dt} = p\cdot dx + q_c(x\cdot dx) - q_a(x) - \Delta T\cdot k_{ca}\cdot dx$$

$$\rightarrow j\cdot c\cdot \Delta T = k_{ca}\cdot \Delta T - q_a\cdot dx = p \quad (1)$$

Where: $c =$ heat capacity of cable per length unit

$\Delta T =$ temperature difference between cable and ambient

$p =$ (ohmic) heat dissipation per length unit in the cable

$q_a =$ heat flow to ambient

$q_c =$ heat flow through cable along x-axis

$k_{ca} =$ the thermal conductance of the cable

For the heat flow $q_c$ it applies:

$$q_c = A \cdot k_{cu} \cdot \Delta T / dx$$

where: $k_{cu} =$ heat conductivity of the conductor

Combining equations (1) and (2), we find:

$$(k_{ca} + j\cdot c) \cdot \Delta T - A \cdot k_{cu} \cdot d\gamma \cdot \Delta T / dx = p \rightarrow$$

$$\Delta T(x) = \Delta T_{0} \cdot e^{-\gamma \cdot x} \quad \text{and} \quad q_c(x) = A \cdot k_{cu} \cdot \gamma \cdot e^{-\gamma \cdot x}$$

where: $\Delta T_{0} = \Delta T(x=0) = p / ((k_{ca} + j\cdot c) / (A \cdot k_{cu}))^{1/2}$

We use these equations to obtain the one-port equivalent Norton network model shown in figure A2.
The Norton heat source $q_{sc}$ equals $q_0$ under the condition that the temperature difference $\Delta T_0$ at the cable is kept to 0 [°C]. We than find:

$$q_{sc} = A \cdot k_{cu} \cdot \gamma \cdot \Delta T_0 = A \cdot k_{cu} \cdot \gamma \cdot p / (k_{ca} + j \cdot \omega \cdot c) = q_{0sc} / (1 + j \cdot \omega \cdot \tau)^{0.5}$$

where: $q_{0sc} = p \cdot (A \cdot k_{cu} / k_{ca})^{0.5}$ and $\tau = c / k_{ca}$

The dissipaction $p$ per unit length in the cable equals: $p = I^2 \cdot \rho$ where $\rho$ is the specific (electical) resistance of the conductor. Using this, we can work out the factor $q_{0sc}$ as:

$$q_{0sc} = R_e \cdot I^2$$

where: $R_e = \rho \cdot (k_{cu} / (A \cdot k_{ca})^{0.5}$

The Norton impedance $Z_{eq}$ equals the ratio of $\Delta T_0$ and $q_{sc}$ under the condition that $q_0 = 0$ [W]:

$$Z_{eq} = \Delta T_0 / q_{sc} = R_e / (1 + j \cdot \omega \cdot \tau)^{0.5}$$

where: $R_e = (A \cdot k_{cu} - k_{ca})^{0.5}$

The Norton heat source and impedance can be approximated by first-order networks as:

$$q_{0} = R_{eq} \cdot I^2 / (1 + j \cdot \omega \cdot \tau_e)$$

and

$$Z_{eq} = R_e / (1 + j \cdot \omega \cdot \tau_e)$$

where: $\tau_e = \tau / \sqrt{3}$

The time-constant $\tau_e$ is chosen such a way that the cut-off frequency of the first order model equals the cut-off frequency of the original model.

Figure A3 shows the thermal RC-network model of the cable.

\[ \Delta T_0 \]

\[ \begin{array}{c}
\begin{array}{c}
R_e = 1 / \sqrt{A \cdot k_{cu} \cdot k_{ca}} \\
C_e = c \sqrt{A \cdot k_{cu} / (3 \cdot k_{ca})} \\
q_{sc} = \frac{R_{eq} \cdot I^2}{1 + j \cdot \omega \cdot \tau_e}
\end{array}
\end{array} \]