Model predictive power distribution in an electric vehicle with a fuel cell

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Abstract. Within the subproject “Intelligent Electric Vehicles with Range Extender in Traffic Systems with Vehicle 4.0” (iREX 4.0), which is part of the joint project “Future Vehicle Technologies in the Open Region Lab” (“Zukünftige Fahrzeugtechnologien im Open Region Lab”, ZuFOR), funded by the Ministry of Science and Culture of Lower Saxony and the Volkswagen Foundation, the research work focuses on cross-linked autonomous electric vehicles with fuel cells serving as range extenders. The aim of the project is the conception of digitized traffic systems that consist of cross-linked autonomous electric vehicles with range extender (RE). This contribution presents an approach for a model predictive power distribution to the energy sources battery and fuel cell considering their specific characteristics.

1. Introduction
The transdisciplinary joint project “ZuFOR” at Ostfalia University comprises three technical subprojects whose focuses are on innovative vehicle technologies in active safety systems for passenger cars, lightweight plastics structures in car manufacturing, and intelligent, digitized, cross-linked electric vehicles with Range Extender, respectively. The technical subprojects are complemented by an integrative subproject designed to facilitate and intensify knowledge transfer between project groups and business, research institutions as well as networks.

The aim of the subproject iREX 4.0 is the development of a flexibly scalable, predictive, electronic vehicle management (peVM) that comprises predictive algorithms for autonomous, energy-optimized operation. As regards operation strategy, there may be three potentials for energy-optimization when an electric vehicle is equipped with a fuel cell as range extender. The first potential lies in the optimization of the route guidance by means of an intelligent navigation algorithm that uses detailed map data comprising height profiles and data from V2X communication to determine the route in consideration of energy consumption and other constraints, e.g., available battery charge and hydrogen quantity or stations for recharging and filling up. The next potential is the optimization of the velocity profile to travel the selected route considering energy consumption as well as static constraints like speed limits and dynamic constraints like traffic lights. The third potential for optimization can be found in the two energy sources. The overall efficiency of the energy supply depends on the power distribution between fuel cell and battery in view of their unequal efficiency characteristics. As the future velocity profile is known, the required vehicle power can be determined in advance and the optimal power distribution can be specified from beginning to end of the journey. The present contribution will detail the approach of the iREX 4.0 subproject aiming at the third optimization potential to gain an energy-optimized power distribution at the level of the on-board power system.
2. Vehicle topology
The vehicle topology of this project (Figure 1) comprises an electric vehicle with one electric drive close to either of the wheels on the rear axle; every drive is mechanically linked to its wheel by a planetary gearbox and disposes of a bi-directional power electronics that will act as rectifier or converter and thus enable both the supply to the drive and the current feedback into the intermediate circuit (IC). The IC can be supplied with energy either by a uni-directional DC converter out of the fuel cell or by a bi-directional one out of the high-voltage battery. By means of the bi-directional DC converter, energy fed into the IC can be transported into the high-voltage on-board electric circuit as and when required. The low-voltage circuit with its own battery for provisioning low-power components is supported by the high-voltage circuit. A conventional hydraulic braking system will ensure safe braking if recuperative braking through the electric drives falls far short because of low speed or narrow machine limits. By means of individual steer-by-wire modules at each wheel of the front axle, it will be possible to carry out not only conventional steering maneuvers but also active toe-angle adjustments. For this purpose a central information processing unit is required that processes sensor- and V2X data and generates reference values for the actuator systems of the vehicle. During an autonomous drive, it will take over the driver’s tasks and ensure safe lateral and longitudinal control.

![Figure 1. Focussed vehicle configuration [1].](image)

3. Methodology
Increasing demands on and the complexity of vehicle systems make a clearly structured design methodology indispensable. The methodology employed is based on a mechatronic structuring of modules and hierarchies through a top-down procedure. The complex overall system is divided into intelligent, encapsulated subsystems, consisting of mechatronic components with defined interfaces, and then structured hierarchically. Figure 2 displays as an example for the focused vehicle topology (chapter 2) the resulting mechatronic structure of the research vehicle FREDY (cf. chapter 6.2 and [2]) comprising four hierarchical levels according to [3]: Mechatronic Function Modules (MFM), Mechatronic Function Groups (MFG), Autonomous Mechatronic Systems (AMS) and Cross-linked Mechatronic Systems (CMS). The MFM constitutes the lowest hierarchical level. It is a mechatronic system that cannot be divided further and consists of a mechanical supporting structure, sensor and actuator system, and information processing. This encapsulated module fulfils a defined functionality, maps the dynamical system behavior and represents kinematics, dynamics as well as the mechatronic functions. A mechanical or informational coupling of several MFMs yields MFGs having their own information processing that can in turn be combined to make up AMSs. Interlinking several AMSs to make up a CMS constitutes the top hierarchical level. A vehicle is an AMS that, through digitization and IoT, can be cross-linked with other vehicles to make up a CMS that is the basis for autonomous driving and nothing else than a cyber-physical system. Following the mechatronic structuring of the overall system, the mechatronic composition is used for developing the individual encapsulated modules in a bottom-up process and integrating them to constitute the higher-level overall system.

The mechatronic structure serves as the basis for deriving the structure of the hierarchical information processing (cf. Figure 3). At the core, there is the predictive electronic vehicle management (peVM) that represents the highest instance in the vehicle. It is part of a cyber-physical traffic system where the vehicle is linked with other traffic participants and the infrastructure via
wireless communication (e.g., in ad-hoc networks according to IEEE 801.11p or mobile radio) and exchanges information with them. The peVM assumes the role of the human driver and plans route guidance on the basis of available information about driving states and environment conditions. Route guidance relies on detailed map data and has to take into account energy consumption, recharging infrastructure as well as actual traffic events to calculate the optimal route and project a velocity profile. It serves for deriving reference values for longitudinal and lateral control. These reference values are transmitted to the subordinated vehicle management, which provides the vehicle-dynamics control and the distribution of variables while comprising further chassis-assistance functions, and to the predictive energy management. The latter itself consists of energy assistance functions for predicting future on-board operation states and power requirements, the thermal energy management for controlling and optimizing heat streams, and the electric energy management with subordinated functions such as management of battery, fuel cell, electric drives or on-board system. These subordinated functions are used for monitoring and safeguarding as well as operating the respective aggregates on a local level. Moreover, electric energy management comprises the power distribution between battery and fuel cell for the purpose of increasing efficiency in the drivetrain.

Every function module with its associated information processing is designed according to the mechatronic development cycle (Figure 4). Theoretical investigation starts out from modelling which results in a physical resp. mathematical model, its behavior and validated parameters. This model is the basis for the model-based systems engineering of control strategies. This method is characterized by early validation and verification so that development time and costs can be reduced. It is done according to Rapid Control Prototyping (RCP) in a consistent, verification-oriented process with Model-in-the-Loop (MiL), Software-in-the-Loop (SiL) and Hardware-in-the-Loop (HiL) simulations.

A virtual test bench (Figure 5) is used for these MiL and SiL simulations. The algorithms of an Electronic Control Unit (ECU) can be tested automatically using a large database of virtual models and test cases. Results are visualized not only in diagrams but also in videos of the vehicle behavior so that the impact of changes to the algorithms can be comprehended directly.

A flexibly configurable HiL test bench (Figure 6) is designed for the purpose of a model-based, consistent design, validation and safeguarding. Its modular configuration enables treating various applications, from parameter identification and validation of simulation models to the testing, verification, and optimization of functions developed in the process. The test bench is based on the vehicle topology detailed in chapter 2. The test bench consists of a real-time module (RTM), a software module (SWM) and several modular test bench modules (TBM). The RTM performs the processing and digitization of the measurement signals from the TBM, computation of the control algorithms on a digital signal processor (DSP), setting reference values for the TBM actuators as well as communication with the TBM whereas the SWM comprises models of components that are not available, control algorithms, and the interface between user and test bench for visualizing the state and test bench control. The models and controllers are uploaded to the DSP via automated code

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**Figure 2.** Mechatronic structuring of FREDY [4].

**Figure 3.** Hierarchical structure of the peVM within a cyber-physical traffic system [1].
generation. The TBM are made up of a fuel cell-, a battery-, a drive- as well as a load- and source-module, all of them operating in encapsulated mode and laid out for following application scenarios:

- **Fuel cell module**: Test of fuel cells for parameter identification.
- **Battery module**: Test and optimization of battery cells and systems with defined climatic conditions, both via DC measurements and electrochemical impedance spectroscopy.
- **Drive module**: Test of el. drives and power electronics, trials and optimization of drive controls.
- **Load and source module**: This auxiliary module yields controllable supply voltages and supply currents as well as controllable load currents for simulating on-board components.

With suitable interfaces in a coupled operation of several test bench modules, many other application scenarios can be used:

- **Battery, fuel cell, and load/source modules**: Test of control concepts for power distribution between battery and fuel cell.
- **Battery, drive, and load/source modules**: Test of recuperation algorithms.
- **Fuel cell, battery, drive, and load/source modules**: Test of the drivetrain, involving fuel cell, battery, drive, and source as well as load that represent further components of the on-board system.

**Figure 4.** Mechatronic development cycle [2].

**Figure 5.** Virtual test bench for MiL and SiL simulations [4].

**Figure 6.** Modular structure of the flexible HiL test bench [1].

### 4. Modeling

This section shows the modeling of the lithium-ion battery and the fuel cell as the basis for the energy-optimized power distribution.

#### 4.1. Battery

Lithium-ion cells are electrochemical energy storages, which can provide electric energy. The lithium-ion battery cell can be described with an equivalent circuit diagram according to [5]. This type of model is distinguished by a high accuracy, relatively easy ways to identify the parameters and a short
computation time, which allows real-time applications. The cell behaves highly nonlinear and the terminal voltage $v$ depends on the current $i$ as well as on the actual state of charge $SOC$, the temperature $T$ and the state of health $SOH$. The effect of the state of health is neglected in this first approach on modelling. The state of charge can be computed with the balance equation (1) with an initial state of charge $SOC_0$, the Coulombic efficiency $\eta_C$ and the battery capacity $C_n$:

$$SOC = SOC_0 + \int \frac{\eta_C i}{C_n} dt$$  \hspace{1cm} (1)

The terminal voltage can be determined from the equivalent circuit diagram (Figure 7). The terminal voltage depends nonlinear on temperature and state of charge and consists of the open-circuit voltage $OCV$, ohmic losses on a serial resistance $R_S$ and the voltages $v_{RC,i}$ on four RC elements to approximate the battery dynamics.

$$v = OCV - R_S i - v_{RC1} - v_{RC2} - v_{RC3} - v_{RC4}$$  \hspace{1cm} (2)

Equation (2) can be used to determine the transfer function of the battery in the frequency domain, which shows the terminal voltage depending on the current:

$$G(j\omega) = \frac{V(j\omega)}{I(j\omega)} = R_S + \frac{R_1}{R_1 C_1 j\omega + 1} + \cdots + \frac{R_4}{R_4 C_4 j\omega + 1}.$$  \hspace{1cm} (3)

Equation (3) shows that the current is the input and the terminal voltage the output of the battery model. The identification to quantify the parameters was performed both in time and frequency domain [6]. Figure 8 shows the OCV depending on the SOC as a result of measurements in time domain (Figure 8a) and the impedance behavior of the batteries at three exemplary SOCs (Figure 8b) as result of an Electrochemical Impedance Spectroscopy.

4.2. Fuel cell

Fuel cells are electrochemical energy sources, which can provide electric energy from hydrogen. A physics-based model of the stationary terminal voltage with an extension of electrical components to approximate the dynamic behavior is used to model the fuel cell (Figure 9), since this model offers a good compromise between accuracy and computational effort compared to 3D models and because it has a reference to the physics in contrast to empirical approaches.

$$E = E^0 + \frac{RT}{2F} \ln \left( \frac{p_{H_2} p_{O_2}^{0.5}}{p_{H_2O}} \right)$$  \hspace{1cm} (4)
describes the potential difference \( E \) between the electrodes as a function of the standard electrode potential \( E^0 \), the fuel cell temperature \( T \) and the pressures \( p_{H_2}, p_{O_2}, p_{H_2O} \). The pressures are controlled by the fuel cell system and therefore considered constant in this work. The general gas constant \( R \) and Faraday’s constant \( F \) are also used in that equation. The terminal voltage of the fuel cell \( u = E - u_{act} - u_{ohm} - u_{conc} \) (5) results from Nernst voltage \( E \) minus activation overvoltage \( u_{act} \), ohmic voltage drop \( u_{ohm} \) and concentration overvoltage \( u_{conc} \). The activation overvoltage can be described using the Tafel equation \( u_{act} = \frac{RT}{2\alpha F} \ln \left( \frac{i}{i_0} \right) \) (6) that uses the charge transfer coefficient \( \alpha \), the current \( i \) and the constant \( i_0 \). The ohmic voltage drop \( u_{ohm} = R_{ohm}i \) (7) represents losses on the internal resistance \( R_{ohm} \). The concentration overvoltage \( u_{conc} = -\frac{RT}{2F} \ln \left( 1 - \frac{i}{i_l} \right) \) (8) has a significant influence on the terminal voltage only at high currents close to the limiting current \( i_l\) due to decreasing concentrations of the working gases as well as time-limited transport processes within the fuel cell. The electrical equivalent circuit diagram (Figure 9) shows the extension of the stationary model with a capacity \( C_{DC} \), which represents the double-layer capacity of the fuel cell. The extended model is a PT1 system \( u_{act} + R_{act}C_{DC}u_{act} = R_{act}i \) (9) with the gain \( R_{act} \) and the time constant \( \tau = R_{act}C_{DC} \) for an approximation of the dynamics. The parameters of the fuel cell are identified by measurements in time and frequency domain gained using the flexible HiL test bench [7] analogous to the battery parameters. Figure 10 shows an exemplary identification result in the time domain.

\[ \text{Figure 10. Exemplary identification result of the fuel cell parameters in time domain [7].} \]

It shows a comparison of measured and simulated polarization voltage and the fuel cell temperature during the measurement. The temperature increases with increasing load and duration starting from the equilibrium and decreases again with decreasing load until the equilibrium is reached again. This behavior is reflected in the polarization voltage, which also assumes higher voltages for higher temperatures. The voltage reaches the equilibrium after the fuel cell returned to its temperature equilibrium. The comparison of measured and simulated polarization voltage shows the high accuracy of the model with the identified parameters. The following section deals with the model predictive power distribution (MPPD) based on the battery and fuel cell models.

5. Model predictive power distribution

5.1. Power prediction

Energy and time optimized velocity profiles (cf. [8]) are the reference values for the longitudinal control of autonomous vehicles. Such an optimized velocity profile is used for calculating a power profile of the vehicle for the entire route, so that the power can be distributed between fuel cell and battery in a next step. At first, assuming constant acceleration, the velocity profile between two nodes is transformed in such a way that the velocity no longer depends on the distance but on time.
prediction (cf. Figure 11), an inverse vehicle-dynamics model is used to determine the tire circumference forces in longitudinal direction $F_{x,i}$ from the predicted velocity profile $v_{\text{pred}}$. By means of inverse tire models, the resulting curves mapping the longitudinal forces are then converted into wheel-angle-speed- and wheel-torque curves, $\omega_{x,i}$ and $M_{x,i}$; an inverse drivetrain model is then used for a prediction of the mechanical and finally electrical driving power profile $P_{\text{pred}}$.

![Figure 11. Structure of the power prediction.](image)

Taking a drive from Ostfalia University in Wolfenbuettel to Ostfalia in Wolfsburg as an example, the map displays the predicted velocity profile (Figure 12a) and the predicted power profile calculated from the latter (Figure 12b). It is obvious that during acceleration both positive power peaks (increase in speed) and negative ones (recuperation) occur whereas in phases of constant velocity the power is also constant. In the following, the predicted power profile will be the ref. value for MPPD.

![Figure 12. Exemplary result of power prediction (b), based on the predicted velocity profile (a) for a drive from Ostfalia in Wolfenbuettel to Ostfalia in Wolfsburg.](image)

5.2. Control algorithm

The optimization problem of the MPC concerns the distribution of the predicted power between battery and fuel cell to minimize energy losses on the whole route until the travel destination is reached. For solving the optimization problem, a model predictive control (MPC) is laid out, because it takes into account the future system behavior and improves it by selecting an optimal sequence of ref. values. The first approach to a MPPD simplifies the problem in that battery and fuel cell voltages are constant and models are linearized. The relevant system states $\tilde{x}_k = [SO\,C_k \ m_{\text{H}_2,k}]$ describe the state of charge of the battery SOC and the filling level of the hydrogen tank $m_{\text{H}_2}$. The vector of manipulated variables $\tilde{u}_k = [i_{\text{bat},k} \ i_{\text{fc},k}]$ contains the currents of the two energy sources that have an effect on the states. Future behavior of the system states can be calculated using the linear state equation

$\bar{x}_{k+1} = A\tilde{x}_k + B\tilde{u}_k$  \hspace{1cm} (12)

This calculation will be performed in the following time steps from $k+1$ to the end of the prediction horizon $k + N_p$, with the results being summed up in the vector of future states

$\bar{x}_k^T = [\tilde{x}_{k+1} \ \tilde{x}_{k+2} \ \cdots \ \tilde{x}_{k+N_p}]$.  \hspace{1cm} (13)

From the current time $k$ to the end of the control horizon $N_u$, which is equated with the prediction horizon $N_p$, the future variables are accumulated in the vector of future manipulated variables

$\bar{u}_k^T = [u_k \ u_{k+1} \ \cdots \ u_{k+N_u-1}] = [\tilde{u}_k \ \tilde{u}_{k+1} \ \cdots \ \tilde{u}_{k+N_p-1}]$.  \hspace{1cm} (14)

From the future manipulated variables, the future overall current

$\bar{i}_k^T = [i_{\text{sum},k+1} \ i_{\text{sum},k+2} \ \cdots \ i_{\text{sum},k+N_p}]$  \hspace{1cm} (15)

can be calculated based on the general correlation
that is used with all time steps. This yields the matrix

\[ t_{\text{sum}} = t_{\text{bat}} + t_{\text{fc}} \]  

that yields the matrix

\[ \bar{I}_k = \begin{bmatrix} 1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 1 \end{bmatrix} \tilde{u}_k. \]  

Under the above-mentioned assumption of the constant voltages, the future overall power
\[ \bar{P}_k = \begin{bmatrix} u_{\text{bat}} & u_{\text{fc}} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & u_{\text{bat}} & u_{\text{fc}} \end{bmatrix} \tilde{u}_k = K \tilde{u}_k \]

of the energy sources can be calculated. The MPC has the aim of distributing the predicted power
\[ \bar{E}_{\text{pred},k} = \begin{bmatrix} P_{\text{pred},k+1} & P_{\text{pred},k+2} & \cdots & P_{\text{pred},k+N_p} \end{bmatrix} \]

between battery and fuel cell over the entire drive while minimizing the energy losses
\[ E_{\text{L},k} = \bar{u}_k^T R \bar{u}_k \]

that accrue until the end of the drive. For reasons of simplification, the losses are assumed to occur only at the internal resistances of the energy sources, comprised in \( R \). The composed cost function
\[ J_k(\bar{u}_k) = g_P(\bar{P}_{\text{pred},k} - \bar{P}_k)^T(\bar{P}_{\text{pred},k} - \bar{P}_k) + g_E E_{\text{L},k} = g_P(\bar{P}_{\text{pred},k} - K \tilde{u}_k)^T(\bar{P}_{\text{pred},k} - K \tilde{u}_k) + g_E \tilde{u}_k^T R \tilde{u}_k \]

is the basis for optimization and cosiders the mean square deviation between the reference and actual values as well as the energy losses. Through a transformation and by neglecting components that cannot be impacted by \( \tilde{u}_k \), the cost function can be converted into the quadratic optimization problem
\[ J_k(\tilde{u}_k) = \tilde{u}_k^T(g_P K^T K + g_E R) \tilde{u}_k - 2g_P \tilde{P}_{\text{pred},k}^T K \tilde{u}_k \]

The optimization has the aim of minimizing the cost function
\[ \min J_k(\tilde{u}_k) = \min \left( \tilde{u}_k^T(g_P K^T K + g_E R) \tilde{u}_k - 2g_P \tilde{P}_{\text{pred},k}^T K \tilde{u}_k \right) \]

by means of an optimal sequence of variables \( \tilde{u}_k \), and taking into account the inequality constraints
\[ N \tilde{u}_k \geq g. \]

The inequality constraints \( g \) comprise the operating limits of battery and fuel cell current as well as the minimum and maximum admissible states (battery SOC and hydrogen in the tank). One drawback of MPC with constraints is the fact that the optimization problem can no longer be solved analytically, thus requiring a numerical solution. There are defined algorithms that can be used for solving quadratic optimization problems. Nonlinear behavior or cost functions that do not refer to a quadratic optimization problem can be solved by means of dynamic programming according to Bellman.

5.3. Results

Figure 13 displays an exemplary first scenario of the MPPD. The predicted power curve that was set as reference value is realized as the sum of fuel cell and battery power (a). The power is divided to the battery (b) and the fuel cell (c) while only the battery is able to store negative power from recuperation. Due to the load of the driving task, the battery SOC (d) as well as the hydrogen stored in the tank (e) decrease. The energy losses reach an overall optimum according the ref. power profile.

![Figure 13](image-url)
Figure 14 displays another exemplary result of the MPPD with reaching a state limit. The same predicted power curve (a) was set as reference value in a second scenario and is again realized as the sum of fuel-cell- and battery power. The overall battery power (c) of the second scenario is lower than in the first one so that in reverse the fuel cell power (d) is higher in the second scenario. This distribution avoids a violation of the lower battery SOC limit of 10 % (e) so that there will be no deep discharging that may damage the battery in the long run. In order to achieve the overall power and to meet this constraint, higher power is extracted from the fuel cell that disposes of enough fuel (f). The energy losses (b) reach an optimum only according the reference power profile and the constraints. Indeed, this optimum is not the overall one that can only be reached with a higher initial SOC (cf. scenario 1).

Figure 14. Exemplary results of the model predictive power distribution incl. reaching a constraint.

6. Realization

6.1. Flexible HiL test bench
Figure 15 displays the realized HiL test bench (cf. chapter 3) with exception of the drive module. At the present stage of development, the individual modules are functioning so that the test bench can be used for tests on every single component. The HiL test bench was used to perform the parameter and system identification as well as the validation and optimization of the battery and fuel cell models. Further work on the project will concentrate on the integration of the components with the aim of realizing the combined applications. Therefore, especially innovative power electronics are under to perform investigations on the MPPD under real-time conditions.

Figure 15. Realization of the flexible HiL test bench [1].

Figure 16. Current state of completion of the research vehicle FREDY.

6.2. FREDY
The Function Carrier for Regenerative Electromobility and Vehicle Dynamics, FREDY, serves the purpose of validating and optimizing vehicle functions in reality when these have been sufficiently
examined and optimized by means of simulations and test bench trials. It is an electric vehicle that conforms to the concept displayed in Figure 1, except for the fuel cell, which will be mounted later. FREDY (Figure 16) disposes of two electric drives close to the wheels that get their power from two lithium-ion battery packs via bi-directional power electronics. A dSPACE MABX II is the central information-processing unit and performs all measurement and control tasks. Future work will include realization, validation and optimization of the MPPD after the integration of the fuel cell to FREDY.

7. Summary and outlook
The present contribution describes the underlying problem and range of tasks in the iREX 4.0 project where intelligent algorithms for an energy-optimal drive of electric vehicles with fuel cells are to be developed. A consistent, model-based design methodology for mechatronic systems was introduced and applied on the iREX 4.0 project. Moreover, a flexibly configurable HiL test bench was presented that will be employed at every project stage, from parameter identification of simulation models to validation and optimization of developed algorithms in a real-time environment. It was a given a brief overview on modeling a lithium-ion battery and a PEM fuel cell in order to achieve a high accuracy combined with a low computational effort. A power profile is predicted based on an optimized velocity profile as reference value for the autonomous driver. This power profile is used by a model predictive control that distributes the overall power to the battery and the fuel cell whilst maintaining the operation limits in order to achieve an optimum concerning the overall energy losses.

Future activities will include extending the MPPD to consider also the non-linear behavior of battery and fuel cell. Moreover, parallel computation of the MPPD using different timescales will be focused; thus, computation for a short time horizon from the actual position will accordingly be performed more detailed with a shorter time frame than a longer time horizon to the end of the journey because the computation for the long period of time has greater uncertainties. Furthermore, we will proceed to realize the MPPD also with the flexibly configurable HiL test bench and the FREDY research carrier.

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