A battery Hardware-in-the-Loop setup for concurrent design and evaluation of real-time optimal HEV power management controllers

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Abstract: We have developed a battery Hardware-in-the-Loop (HIL) setup, which can expedite the design and evaluation of power management controllers for Hybrid Electric Vehicles (HEVs) in a novel cost- and time-effective manner. The battery dynamics have a significant effect on the HEV power management controller design; therefore, physical batteries are included in the simulation loop for greater simulation fidelity. We use Buckingham's Pi Theorem in the scaled-down battery HIL setup to reduce development and testing efforts, while maintaining the flexibility and fidelity of the control loop. In this paper, usefulness of the setup in parameter identification of a simple control-oriented battery model is shown. The model is then used in the power management controller design, and the real-time performance of the designed controller is tested with the same setup in a realistic control environment. Test results show that the designed controller can accurately capture the dynamics of the real system, from which the assumptions made in its design process can be confidently justified.

Keywords: cost-effective battery HIL; hardware-in-the-loop; HEV; hybrid electric vehicle; optimal power management controller; battery identification; component scaling; model-based controller design.

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1 Introduction

HEVs have proven to be more fuel efficient than conventional vehicles. However, higher fuel economy cannot be achieved without an intelligent plan (the so called *supervisory* or *power management controller*) to decide on the power flow in the hybrid electric powertrain. Design and testing of such optimal power management controllers has been an interesting research topic in the past decade.

The major challenges in designing an optimal HEV power management controller are, first, the complexity of the system under control, and second, the uncertainty associated with the system input (i.e., the driver commands). The power management controller should command each component in such a way that the fuel consumption and/or emission is minimised while the driver command is followed, and the physical constraints of the system are not violated. In the early stages of the development of HEVs, rule-based power management controllers were used; these plans, although being robust and simple to implement, do not result in optimal behaviour and are difficult to tune.

Studies show that even a small reduction of 3% in HEV fuel consumption will save at least 6.5 million gallons of gas annually in USA (Gonder, 2008). This has been the motivation for many researchers to invent model-based controllers in recent years, as these controllers have the potential to provide higher fuel economy compared to rule-based controllers (Sciarretta and Guzzella, 2007).

One promising approach for the development of an optimal HEV power management strategy is Model Predictive Control (MPC) (Borhan et al., 2010; Taghavipour et al., 2012; Sampathnarayanan et al., 2009). In MPC, the controller assigns the component set-points based on the dynamics and the inputs of the system. Thus, optimality of an MPC controller strongly depends on the accuracy of the model inside the controller. Similarly, Pontryagin's Minimum Principe (PMP) has shown strong potential in the development of optimal power management strategies (Serrao et al., 2011; Razavian et al., 2012a, 2012b; Kim et al., 2011, 2012; Cipollone and Sciarretta, 2006; Stockar et al., 2010; Serrao and Rizzoni, 2008). In PMP, the integral minimisation problem is reduced to local minimisation of the Hamiltonian (Kirk, 2004), which in turn, is reduced to tuning of the costates (Kim et al., 2012; Ambuhl and Guzzella, 2009). Proper tuning of the costate requires a correct representation of powertrain components, especially the electrical storage system.

In recent studies (Razavian et al., 2012a, 2012b), we have developed real-time optimal controllers for a series HEV based on the solution of PMP for an off-line optimal control problem. The controllers have been shown to be mathematically optimal. However, the usefulness of these controllers, just as any other model-based controller, depends on the models upon which they are designed. On one hand, the control-oriented models must be as simple as possible to keep the computations manageable by the Electronic Control Units (ECUs), and on the other hand, they should be able to represent the dynamics of the system accurately enough.

To evaluate the performance of such designed controllers, software simulations can be employed (Razavian et al., 2012b). Although virtual modelling of the HEV powertrain components can provide valuable information about the system behaviour, it may fail to depict all aspects of the control loop. Some aspects such as communication delays between different ECUs, real-time performance, and computational time for the power management controller cannot be easily simulated in the all-software environments. Moreover, the virtual models are only a representation of the real systems, and a certain level of error is unavoidable.

To study the real-time performance of the control loop, and to further enhance the fidelity of the simulations, physical components of the system can be included in the simulation in a Hardware-in-the-Loop (HIL) setup. In HIL simulations, usually the controller is programmed into a rapid-prototyping unit and the high-fidelity model of the system is solved in real-time. In addition, the critical components of the system can be realised as full-size or scaled physical components. In this work, because of the crucial impact of the electrical storage system in HEV power management controller design, physical batteries are included in the setup (sometimes called *component-in-the-loop* simulation).

The size of the components in HIL setups requires careful consideration. Unless the setup is designed for a specific target vehicle, the components have to be scaled properly to achieve the desired behaviour in the target vehicle. One approach for component scaling is Buckingham's Pi Theorem in which the inputs, the outputs, or other parameters of the components are scaled in such a way that the dimensionless groups of parameters in the target and scaled components are equal Brand (1957). In the application of HIL for hybrid electric vehicles, Pi Theorem is shown to be an effective method for scaling the components to arbitrary sizes (Petersheim and Brennan, 2009, 2008). In our scaled battery HIL, the same approach is taken to scale the battery cells to a full size battery pack.

In an HIL simulation, since some parts of the system are realised as virtual models and some other parts are physical systems, they have to work at the same time scale; otherwise, some dynamics and features of the system may not be captured correctly. Therefore, real-time simulation of the virtual model is essential in HIL simulations. For such applications, usually fixed-step solvers are more suitable, as the variable-step solvers do not provide a deterministic solution time. On the other hand, the fixed-step solvers show poor performance in stiff problems. Because of the absolute necessity for real-time operation, the fixed step solvers are preferred in HIL simulations. In this case, one approach to avoid stiff problems is to use the physical component instead of the stiff virtual model (e.g., using hydraulic circuits in Dalfio et al. (2006) and Lee and Suh (1999)).

In the area of simulation, HIL has been used extensively. In Dalfio et al. (2006) and Xiao-kun et al. (2011), the HIL setups were used for simulation and feasibility study of an electro-hydraulic system and a hybrid electric tram, respectively. An HIL setup was also used in Gauchia and Sanz (2010) to increase the fidelity in simulation of a fuel cell vehicle. To find the efficiency maps and for model verification, an HIL setup (containing all the components of an HEV) was used in Hentunen et al. (2010). The campus-wide setup in Petersheim and Brennan (2009), including several components in different labs across the campus, was used to simulate different component sizes in an HEV powertrian.

HIL simulation is a very handy tool in controller validation as well. For HEV controller simulation, HIL setups have been used in Petersheim and Brennan (2009), Grondin et al. (2011), Hung et al. (2010), McGee (2003), Ramaswamy et al. (2004), Timmermans et al. (2007), Wang et al. (2012), Xiaowei et al. (2010) and Xu et al. (2009). HIL setup can also be used for lower-level controller development such as electric motor controller (Dufour et al., 2007), Integrated Starter/Generator (ISG) controller (Shen et al., 2010), semi-active suspension controller (LAM and Liao, 2001), and engine controller (Wagner and Furry, 1992; Lee et al., 2003). For better EV controller design, road/tyre interaction was realised in an HIL setup (Ma et al., 2011).

In this work a battery HIL setup is developed, which facilitates the design and evaluation of an HEV power management controller by integrating them into a novel unified structure, in which the controller design and the realistic real-time evaluation occur concurrently. The setup employs a rapid-prototyping ECU as the power management controller, a powerful real-time computer to solve the virtual vehicle model, and a real-time battery cycler for incorporating a physical battery into the simulations. The setup reduces the time and cost of development of HEV power management controllers, as it simultaneously gives the flexibility of software simulations that is essential in the controller design, and greater fidelity of the control loop that is required in the evaluation process. In the model-based controller design process, the setup is used to derive an accurate controller-oriented model. We also show how the parameters of the derived model and the battery cycler should be scaled using Buckingham's Pi Theorem to achieve accurate representations of the full size battery pack. Finally, real-time performance of the designed controller is evaluated with enhanced fidelity using the setup.

The rest of this article is organised as follows: Section 2 summarises the basics of our optimal controller for a series HEV. In Section 3, the details of the battery HIL setup are presented. Section 4 shows how the setup can be used to find the control-oriented model, and Section 5 shows how the battery parameters can be scaled using Buckingham's Pi Theorem. Finally, Section 6 presents the HIL simulation results and Section 7 concludes the paper.

2 Real-time optimal controller for a series HEV

In a previous study (Razavian et al., 2012b), an optimal controller for a series HEV has been developed. Here a brief description of the controller is presented.

For the series HEV shown in Figure 1, a simple control-oriented model is assumed. In this control-oriented model, the battery is modelled according to equation (1) in which the battery parameters, V_{oc}, R and Q, are assumed to be independent of battery state of charge, SoC. This assumption will be justified in the later sections. (For a complete list of symbol descriptions please see the Nomenclature at the end of the paper).

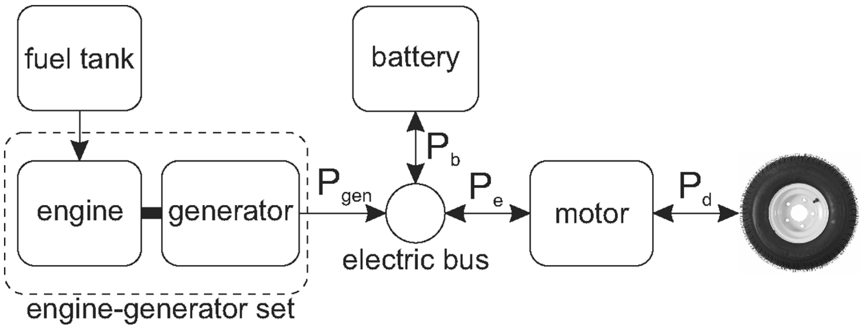
$$\dot{\mathrm{SoC}} = \frac{-V_{oc} + \sqrt{V_{oc}^2 - 4RP_b}}{2RQ}. \tag{1}$$

The engine-generator set is also modelled in a simple manner according to:

$$\dot{m} = \alpha P_{\text{gen}} + \beta \tag{2}$$

with α and β being constants.

Figure 1 Schematic of the series HEV



The electric motor is modelled as a power transducer, converting from electrical power to mechanical power and vice versa, with constant efficiency:

$$P_e = P_d\, \eta_m^{-\text{sign}(P_d)}. \tag{3}$$

Finally, in the electric bus, the powers from the battery and the generator add together at 100% efficiency to form the total electric power:

$$P_{\text{gen}} + P_b = P_e. \tag{4}$$

To form the optimal control problem, the cost function of equation (5) is considered. Pontryagin's Minimum Principle is then applied to this optimal control problem and it can be shown that the fuel-optimal solution is according to equation (6).

$$J = \int_0^{t_f} \dot{m}\, \mathrm{d}t \tag{5}$$

$$P_b^* = \begin{cases} P_{\max} & P_{\max} < \bar{P} \\ \bar{P} & P_{\min} < \bar{P} < P_{\max} \\ P_{\min} & \bar{P} < P_{\min} \end{cases}. \tag{6}$$

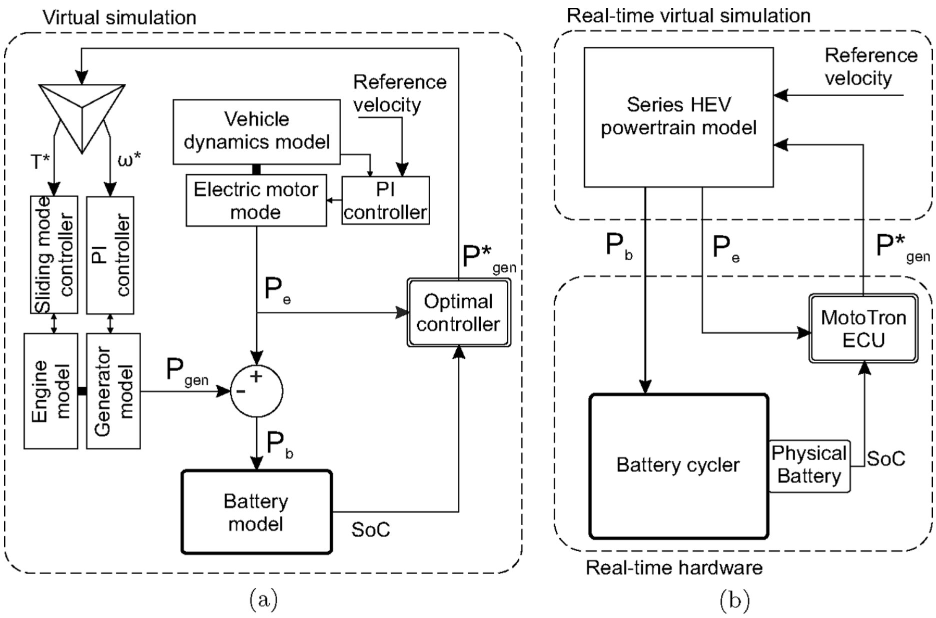
In the above control strategy, $P_{\min}$ and $P_{\max}$ are the time-varying maximum and minimum allowable battery power, and $\bar{P}$ is a constant value that should be tuned according to driving conditions to achieve charge sustenance. The value of $\bar{P}$ can be approximated with the method presented in Razavian et al. (2012b).

Once the optimal battery power is determined, the power management controller calculates the optimal generator power according to equation (7), and this reference generator power is sent to the engine-generator set.

$$P_{\text{gen}}^* = P_e - P_b^* \tag{7}$$

The performance of the designed controller can be tested by applying it to a high-fidelity model of the series HEV powertrain (Razavian et al., 2012b; Dao et al., 2011); the schematic of the control loop in virtual simulations is shown in Figure 2(a). The high-fidelity series HEV model in this *all-simulation* environment is developed in MapleSim, and consists of the engine-generator set, a multibody vehicle dynamics model, the electric motor, and the battery. The engine in this model is a mean-value engine model (Saeedi, 2010), and is torque-controlled by a sliding-mode controller (Razavian et al., 2012b). The engine is coupled to a speed-controlled permanent-magnet DC generator. The torque and the speed set-points of the engine-generator set (T^* and ω^*) come from the optimal power management controller. Simultaneously, the 14-degree-of-freedom vehicle dynamics and traction motor models work together to drive the vehicle according to the reference velocity profile. The difference in the required power of the electric motor, P_e, and the generator output power, P_{gen}, is the amount of power that the battery should deliver or absorb. This battery power, P_b, is then fed to the chemistry-based Li-ion battery model (Dao et al., 2012), from which the battery *SoC* is calculated.

Figure 2 (a) The control loop for the series HEV power management controller, in the all-simulation environment and (b) HIL simulation setup with ECU and physical battery



Since such a virtual simulation is done in one solver, the time scale of the controller and all parts of the model is the same; thus, real-time behaviour of the controller cannot be evaluated properly. To study the real-time performance of the controller, communication issues, and computational limitations, an HIL simulation can be employed. Moreover, modelling error is unavoidable in simulations; thus, for a more accurate simulation, the battery model in the powertrain is replaced with physical battery cells, and a real-time battery cycler is used to drive the physical battery according to powertrain requirements (see Figure 2(b)). In the following section, the details of the HIL setup is presented.

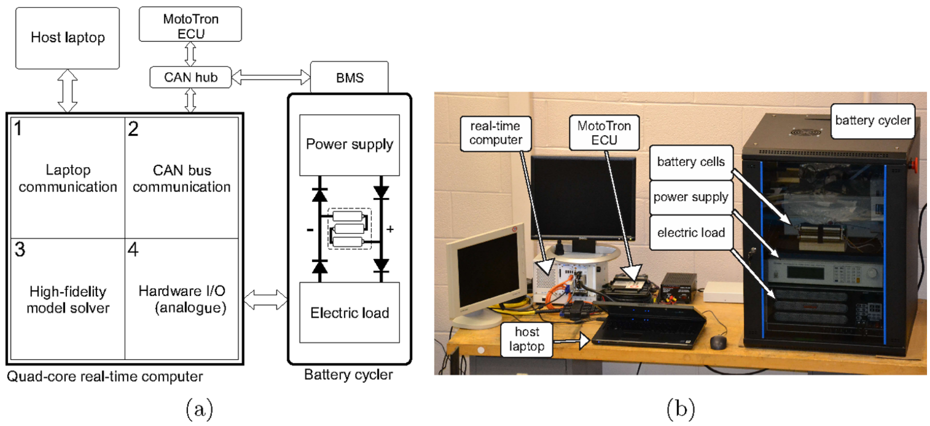
3 Hardware-in-the-Loop setup

The three core components in this HIL setup are:

- an independent processing unit to run the controller procedure
- a powerful real-time computer to run the plant model
- a real-time battery cycler to include physical battery cells in the simulations.

Figure 3 shows the components in the HIL setup.

Figure 3 (a) The schematic of the battery HIL setup and (b) the setup developed (see online version for colours)



It is worthwhile to mention that the battery HIL setup developed is a scaled-down battery test bench – the battery under testing is not the same size as the battery pack in vehicles. Although in such a scaled simulation there is a small amount of error due to component scaling, the greater flexibility of the setup makes it ideal for development purposes. On the other hand, when the full-size battery pack is used, the results are only accurate for that particular battery pack, and simulating other battery sizes is not possible without the same scaling error. Therefore, working with a scaled-down battery test bench is not only more cost-effective, but it also provides the flexibility required for research and development purposes.

The real-time battery cycler consists of a power supply (Chroma 62024P) and an electric load (Ametek Sorensen SLH), which charge and discharge the battery cells (three GAIA 7.5Ahr Li-ion cells in series) in real-time, and according to powertrain simulation requirements.

For our HIL simulation, the designed controller is programmed into an ECU from MotoTron. The automotive-based design of the ECU makes it an ideal choice for the HEV power management controller applications. The same high-fidelity powertrain model that had been previously used is solved deterministically by one core of a quad-core real-time computer (a National Instruments PXI computer) to provide the accurate sampling that the controller requires. The real-time computer is also responsible for controlling and facilitating the communications between different hardware, including the real-time battery cycler, the

Battery Management System (BMS), the MotoTron ECU and the user interface (the host laptop), as shown in Figure 3(a).

The communication channel between the ECU, the plant (virtual model in the real-time target), and the BMS is the Control Area Network (CAN). The real-time computer controls the battery cycler via a DAQ card and the battery cycler's analog interface.

As a result of the flexibility of the setup, the process of design and verification of the HEV power management controllers can be done in a very time- and cost-effective way. The calibratable build of the ECU enables real-time tuning of controller parameters. Moreover, high-fidelity powertrain models can be modified and re-deployed into the real-time computer very efficiently to accommodate, for example, different HEV architectures and component sizes (for an example, see Taghavipour et al. (2012)). Lastly, by employing the real-time battery cycler, real-time model solver, and realistic ECUs, it is possible to simulate the control loop with great accuracy, and without losing any real-time dynamics of the system, which is of great importance in rigorous evaluation of the HEV power management controllers.

In the following sections, the application of the HIL setup in effectively integrating the processes of design and evaluation of the HEV power management controller is presented.

4 Battery identification

The development of HEV power management controllers is greatly affected by the properties of different components in the powertrain. The battery is one of the most important components in a hybrid electric powertrain, and should be examined very closely before designing the power management controllers.

To design a better controller, an accurate control-oriented model that is tailored for a specific battery pack is essential. To identify the parameters that give the best representation of the cells, a parameter identification study has to be done on the battery.

As the developed battery HIL setup employs a scaled battery module, it can greatly reduce the time and cost of the development of HEV power management controllers. In this process, first, a simple control-oriented model for the few battery cells is found; then the model is scaled up to the target size. In this way, only a few battery cells is required for parameter identification, but the model can be scaled to any battery size, without a compromise in control-oriented model accuracy.

The controller-relevant parameter identification can be done off-line. In off-line identification methods, the system is excited, and the outputs are stored as a series of timed signals. The stored data is later compared with the output of the control-oriented model.

For the power management controller of Section 2, the battery control-oriented model of which the parameters should be identified is given in equation (1). The parameters to be identified are $[V_{oc}, R, Q]$ with P_b and SoC being the input and the output, respectively.

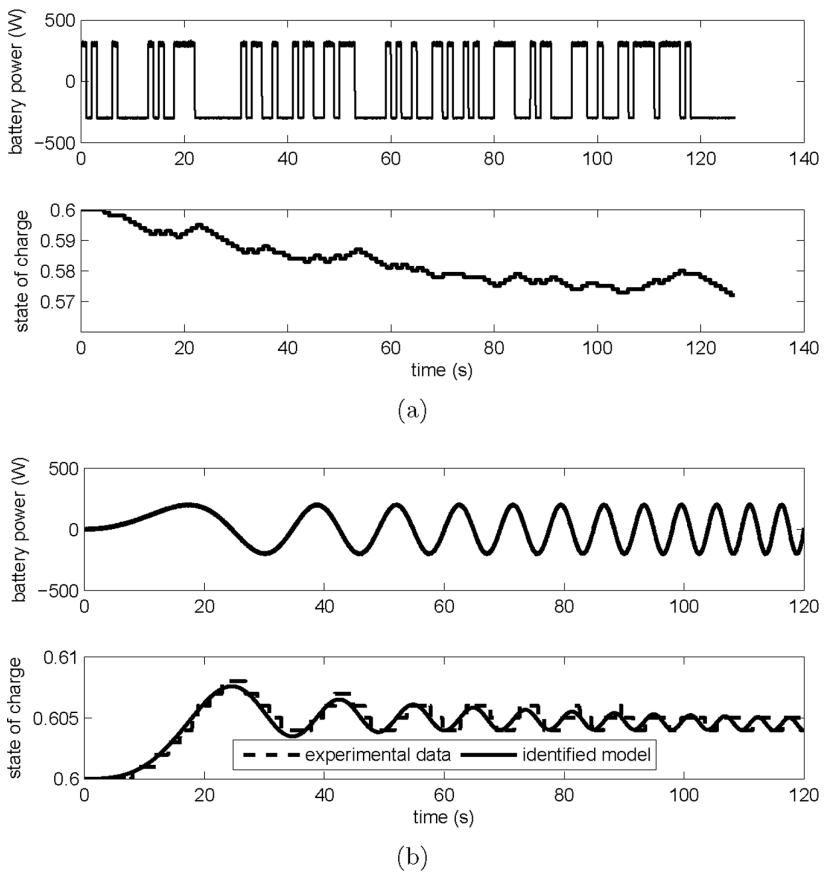
In this study, the excitation power input is chosen as a Pseudo-Random Binary Sequence (PRBS), which contains a broad range of frequencies. The PRBS power input to the battery cells and the change in their state of charge are shown in Figure 4(a).

Matlab's optimisation toolbox is used to find the set of parameters that make the model in equation (1) give close results to the experimental data of Figure 4(a). Among the optimisation algorithms in Matlab, the Genetic Algorithm (GA) is one of the global optimisation methods that can solve constrained optimisation problems, and it is used in this parameter identification process. In this optimisation problem, the objective function to be minimised is the sum of the square of error in each time step:

$$\text{error} = \sum \left(SoC_{\text{model}} - SoC_{\text{experiment}}\right)^2 . \tag{8}$$

Since the parameters of the model in equation (1) have physical meaning, they cannot assume any number. For example, the open circuit voltage has to be close to the terminal voltage of the cells. Therefore, the lower limits presented in Table 1 are specified for the parameters in the optimisation problem. Table 1 also presents the solution of the GA algorithm, with the initial population of $V_{oc} = 10.6$ V, $R = 0.01\ \Omega$, $Q = 30,000$ As, population size of 100, and 100 generations.

Figure 4 The excitation input (P_b) and the resulting output of battery (*SoC*) used for: (a) parameter identification and (b) for model validation



To validate the identified model, the batteries are excited with a different input (a chirp signal). The input power and the comparison of the state of charge between the identified battery model and the experimental data are shown in Figure 4. It can be seen that the identified model can provide close behaviour for different input frequencies. Thus the identified parameters can be used in the controller design process.

Once the control-oriented model for the three battery cells is found, it can be scaled to any target battery size. The process of scaling battery parameters is the subject of the next section.

Table 1 Parameters in the identification problem

Parameter	*Lower boundary*	*Identified value*	*Nominal value*
R	1 mΩ	21 mΩ	19.5 mΩ
V_{oc}	10 V	10.699 V	10.80 V
Q	100 As	29,729 As	27,000 As

5 Battery scaling in the HIL setup

Our battery HIL is a scaled-down setup. This means that the battery parameters, inputs, and outputs need to be scaled properly to get reasonable results. The battery scaling in this work has different aspects. First of all, the battery cells are simulating a full size battery pack; therefore, to get correct results, the input and output of the battery cycler (battery power and SoC, respectively) should be scaled appropriately. Moreover, for controller design, the identified control-oriented model of the battery cells should be scaled up to find the battery model of the target size.

Dimensional analysis is a well-established method, especially in fluid and thermal systems, to relate phenomena that are similar in behaviour but different in parameters. In this study, Buckingham's Pi Theorem (Brand, 1957) is used to map parameters of batteries of different sizes. The approach chosen here is similar to that in Petersheim and Brennan (2009).

The first two columns of Table 2 give the six parameters that need to be considered in battery analysis, as well as their dimensions in terms of four fundamental units: [M]: mass, [L]: length, [T]: time, and [A]: current.

Table 2 Important parameters in battery analysis, their dimensions, and the corresponding dimensionless groups

Parameter	*Dimension*	*Related Pi group*
P	$[M][L]^2[T]^{-3}$	Primary
I	$[A]$	Primary
τ	$[T]$	Primary
V	$[M][L]^2[T]^{-3}[A]^{-1}$	$\pi_1 = P.V^{-1}.I^{-1}$
Q	$[A][T]$	$\pi_2 = I.t.Q^{-1}$
R	$[M][L]^2[T]^{-3}[A]^{-2}$	$\pi_3 = R.I^2.P^{-1}$

The battery state of charge is another important parameter in battery analysis; however, it is a dimensionless parameter by itself, and we consider it as the output of the system. As long as other dimensionless groups of the systems are the same, the state of charge of the two systems will also prove equivalent. The battery power is the input to the battery cycler, and it is the parameter that must be scaled properly before being used to drive the battery. The final goal of this dimensional analysis is to identify such a scaling factor for the battery power.

Since the dimensional bundle of $[M][L]^2$ appears together, it can be considered as one fundamental unit, reducing the number of units to 3; therefore, the Pi Theorem states that the system (battery) can be presented by the $6 - 3 = 3$ dimensionless groups (Brand, 1957). There is no unique set of dimensionless groups, and in this analysis, τ, I, and P are chosen as the primary parameters. For the remaining parameters, dimensionless groups of π_1, π_2, and π_3 are formed and presented in the last column of Table 2.

5.1 Battery scaling for HEV simulation

In this experimental setup, three battery cells represent the full-size battery pack. As both systems have the same chemistry, the dynamics of the two systems are similar. The characteristic time, τ, is chosen to be the discharge time, which is related to the battery power and capacity. Since the battery pack and the cells in the HIL setup should behave similarly, the following relations have to be satisfied:

$$\pi_{1BP} = \pi_{1\mathrm{HIL}} \tag{9}$$

$$\pi_{2BP} = \pi_{2\mathrm{HIL}} \tag{10}$$

$$\pi_{3BP} = \pi_{3\mathrm{HIL}}. \tag{11}$$

In the above relations, the battery pack and the cells are denoted by the subscripts $_{\mathrm{BP}}$ and $_{\mathrm{HIL}}$, respectively. Substituting the Pi relations in Table 2 leads to:

$$\left[\frac{P}{VI}\right]_{BP} = \left[\frac{P}{VI}\right]_{\mathrm{HIL}} \Rightarrow P_{\mathrm{HIL}} = \frac{V_{\mathrm{HIL}}}{V_{BP}}\frac{I_{\mathrm{HIL}}}{I_{BP}}P_{BP} \tag{12}$$

$$\left[\frac{I\tau}{Q}\right]_{BP} = \left[\frac{I\tau}{Q}\right]_{\mathrm{HIL}} \Rightarrow \frac{I_{\mathrm{HIL}}}{I_{BP}} = \frac{Q_{\mathrm{HIL}}}{Q_{BP}}\frac{\tau_{BP}}{\tau_{\mathrm{HIL}}} \tag{13}$$

$$\left[\frac{RI^2}{P}\right]_{BP} = \left[\frac{RI^2}{P}\right]_{\mathrm{HIL}} \Rightarrow \frac{P_{\mathrm{HIL}}}{I_{\mathrm{HIL}}^2} = \frac{P_{BP}}{I_{BP}^2}\frac{R_{\mathrm{HIL}}}{R_{BP}}. \tag{14}$$

By combining equations (12) and (13), one relation for power and capacity can be found:

$$P_{\mathrm{HIL}} = \left[\frac{V_{\mathrm{HIL}}}{V_{BP}}\frac{Q_{\mathrm{HIL}}}{Q_{BP}}\frac{\tau_{BP}}{\tau_{\mathrm{HIL}}}\right]P_{BP}. \tag{15}$$

As the simulations have to be in real-time, the characteristic times of both systems are equal, and the scaling factor is reduced to:

$$\frac{P_{\mathrm{HIL}}}{P_{BP}} = \frac{V_{\mathrm{HIL}}}{V_{BP}}\frac{Q_{\mathrm{HIL}}}{Q_{BP}}. \tag{16}$$

Therefore, the battery power has to be scaled according to equation (16) before it is sent to the battery cycler to drive the battery cells.

It is important to notice that it may not be possible to map one system to the other by just a simple scaling. In this case, once the power is scaled according to equation (16), the last Pi relation, equation (14), may or may not be satisfied. This is because the internal resistance of the battery is an independent parameter and may not be scalable. To better understand this situation, assume two battery cells with the same capacity and voltage, but different internal resistances. The difference may be due to build effects, battery wear, etc. As all of the parameters but the resistance are the same, the first two Pi groups, equations (12) and (13), are essentially the same for the two batteries, but nothing can be done to make equation (14) equal.

This apparent inconsistency with battery Pi groups can be solved by involving more parameters, such as an electro-chemical parameter; however, this type of analysis is out of the scope of this work, and the sole power scaling meets our requirements.

The Li-ion cells in the HIL setup are used to simulate HEV battery packs. The nominal values of the HIL battery parameters and the nominal values of a full-size battery pack (Lexus RX400-h) are presented in Table 3. With these parameters, the scaling factor can be calculated according to equation (17).

$$\frac{P_{\mathrm{HIL}}}{P_{BP}} = \frac{V_{\mathrm{HIL}}}{V_{BP}}\frac{Q_{\mathrm{HIL}}}{Q_{BP}} = \frac{10.8\ \mathrm{V}}{288.0\ \mathrm{V}} \times \frac{7.5\ \mathrm{Ahr}}{6.5\ \mathrm{Ahr}} = 43.27 \times 10^{-3}. \tag{17}$$

This means that the battery power calculated from the virtual HEV simulation has to be reduced by a factor of 43.27×10^{-3} before it is sent to the battery cycler. In this way, the output of the battery cycler (*SoC*) will be the same as a full-size battery pack.

Table 3 Nominal battery parameters used for scaling

Parameter	*RX400-h battery pack*	*GAIA cells*
Voltage (V)	288.0	10.8
Capacity (Ahr)	6.5	7.5

5.2 *Control-oriented model scaling for controller design*

As was mentioned in the beginning of this section, for controller design purposes, the identified control-oriented model for the three battery cells should be scaled properly to a battery of target size.

The target battery in this study is the battery pack in a Lexus RX400-h vehicle with the nominal values specified in Table 3. The identified capacity and voltage of the battery cells can be scaled proportional to the nominal values, as in equations (18) and (19).

$$\frac{Q_{\mathrm{HIL}}}{Q_{BP}} = \frac{Q_{ID}}{Q_{COM}} \Rightarrow Q_{COM} = Q_{ID} \times \frac{Q_{BP}}{Q_{\mathrm{HIL}}} = 7.16\ \mathrm{Ahr} \tag{18}$$

$$\frac{V_{\mathrm{HIL}}}{V_{BP}} = \frac{V_{ID}}{V_{COM}} \Rightarrow V_{COM} = V_{ID} \times \frac{V_{BP}}{V_{\mathrm{HIL}}} = 285.3\ \mathrm{V}. \tag{19}$$

In these relations, the nominal cell parameters in the battery HIL are denoted by the subscript $_{\mathrm{HIL}}$, nominal full-size battery pack parameters by the subscript $_{BP}$, identified parameters by the subscript $_{ID}$, and scaled-up control-oriented model parameters by the subscript $_{COM}$.

To properly scale the resistance, the new dimensionless parameter in equation (20) can be used to relate the identified parameters to the scaled-up control-oriented model.

$$\pi_4 = \frac{RQ}{V\tau}. \tag{20}$$

Again, as the simulations should have the same time scale, the characteristic times are equal, and the resistor can be scaled according to equation (21).

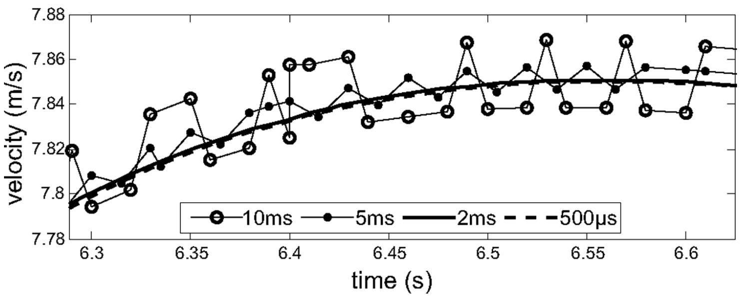
$$R_{COM} = \frac{V_{\text{HIL}}}{V_{ID}} \frac{Q_{ID}}{Q_{\text{HIL}}} R_{ID} = 646.6 \text{ m}\Omega. \tag{21}$$

6 HIL simulation results

In every numerical simulation, the process of convergence study is of great importance. It is essential that the simulation results be free of numerical errors such as integral error and discretisation of simulation time. On the other hand, reducing time steps and integration tolerances increases the computational time, and it is possible that the simulation could fall behind real-time requirements.

To solve the high-fidelity model in the HIL setup, the explicit third order Runge-Kutta integrator is used. The result of such an explicit method converges to the correct solution by reducing the time step. When the solution changes negligibly with reducing the time step, it can be inferred that the solution has converged. Figure 5 shows the result of the convergence study conducted for solving the high-fidelity model in LabVIEW. It can be seen that the time step of 2 ms gives satisfactory results, hence is used in this simulation.

Figure 5 The simulation results for different step sizes



With the developed setup, a full HIL test can be done on the designed controller. Figure 6 shows the tracking performance of the engine-generator set in the virtual model simulation. As a result of the close tracking of the engine-generator set, the reference battery power (the set-point to the battery cycler) closely follows the optimal trajectory that the optimal controller had calculated for the FTP75 drive cycle. Figure 7 also shows that the battery cycler can very well track the set-points. Therefore, one can conclude that the actual battery in powertrain will behave very similar to the simple control-oriented model.

Figure 6 Tracking performance of the lower level controllers of the engine-generator set (see online version for colours)

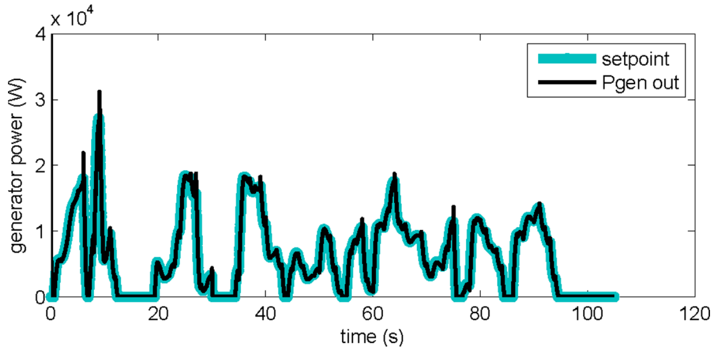


Figure 7 Battery power in the HIL simulation (see online version for colours)

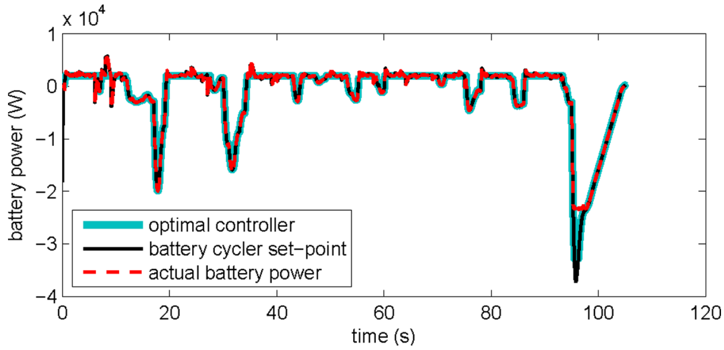
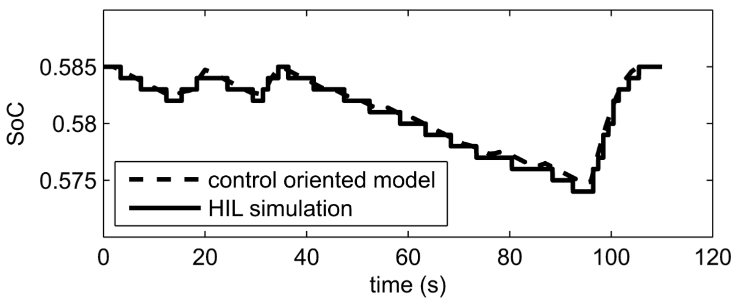


Figure 8 shows the state of charge trajectory of these cells, and what the controller had predicted based on the control-oriented model, for the first part of the FTP75 drive cycle. As can be seen, the controller can successfully predict the battery's behaviour, using the control-oriented model.

Figure 8 HIL simulation results for the state of charge trajectory for the first part of the FTP75 drive cycle



It should be noted that the Li-ion battery parameters, unlike NiMH batteries, change with variations of state of charge. However, in this FTP75 simulation, and in general, in every

HEV operation, the variation of state of charge is small; thus the battery parameters remain very close to the identified parameters. This assumption that was made in the controller design process can now be justified by our HIL simulation results.

As the battery – the most critical component of the powertrain – behaves as predicted by the control-oriented model, one can examine such results and conclude that the optimal controller is indeed able to predict the optimal behaviour of the system (Razavian et al., 2012b). Since the lower-level controllers can force the system to follow the optimal controller set-points (see Figures 6 and 7), the behaviour of the system with the use of the optimal controller is, therefore, optimal.

7 Conclusions

This paper presented the development of a battery HIL setup which can reduce the time and cost of the development of HEV power management controllers. By employing a scaled-down battery cycler in the HIL setup, an accurate control-oriented model was found, which was scaled to arbitrary target battery size without loss in accuracy, using Buckingham's Pi Theorem.

With this control-oriented model, the power management controller was designed. To test the controller, it was programmed into a rapid-prototyping ECU in the HIL setup. A real-time computer was used to solve the virtual high-fidelity models of the components in the powertrain. For the HEV battery, the physical battery in the HIL setup was scaled and driven by the battery cycler in real-time to enhance the accuracy of the simulation.

The HIL results showed that the identified control-oriented model can accurately capture the important dynamics of the system, and as the lower level controllers of different components ensured tracking of the set-points, the outcome of the controller was according to the control-oriented model, and therefore, optimal.

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Nomenclature

α	Engine constant
β	Engine constant
η_m	Total driveline efficiency
π_1	Pi group related to battery voltage
π_2	Pi group related to battery capacity
π_3	Pi group related to battery resistance
π_4	Modified Pi group related to battery resistance
τ	Characteristic time
τ_{BP}	Characteristic time in the full-size battery pack
τ_{HIL}	Characteristic time in HIL setup
SoC	Battery state of charge
I	Current
I_{BP}	Full-size battery pack current
I_{HIL}	Battery current in HIL setup
J	Cost function
P	Power
P_b	Battery power
P_e	Electric power demand
P_{BP}	Battery power in full-size battery pack
P_d	Mechanical power demand at wheels
P_{gen}	Generator output power
P_{HIL}	Battery power in HIL setup
Q	Battery capacity
Q_{COM}	Battery pack capacity in control-oriented model
Q_{BP}	Nominal full-size battery pack capacity
Q_{HIL}	Nominal battery capacity in HIL setup
Q_{ID}	Identified battery capacity in HIL setup
R	Battery equivalence series resistance
R_{COM}	Battery pack resistance in the control-oriented model
R_{BP}	Full-size battery pack resistance
R_{HIL}	Battery resistance in HIL setup
R_{ID}	Identified battery resistance in HIL setup
V	Voltage
V_{COM}	Battery pack voltage in control-oriented model
V_{BP}	Nominal full-size battery pack voltage
V_{HIL}	Nominal battery voltage in HIL setup
V_{ID}	Identified battery voltage in HIL setup
V_{oc}	Battery open-circuit voltage