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Experimental validation of a general energy storage modelling approach (Part III)

Cong-Toan Pham, Daniel Månsson

KTH Royal Institute of Technology, Electromagnetic department, Teknikringen 31, 11428 Stockholm, Sweden

Abstract

Current challenges in the electric grid progression demand energy storages to cope with any imbalances between supply and demand side. Application possibilities of energy storages are numerous, but the requirements vary from case to case. However, not every storage technology operates equally to be useful in any situation. In fact, the feasibility of energy storages depend on their technical characteristics, i.e., for example efficiency, response times, power rating and capacity for a selected application. Comparing and assessing different storage options is imperative for decision-making, which requires an in-depth understanding of the technology and its dynamics. Hence, a general model approach of energy storages as equivalent circuit models has been proposed to unify and analyze storages of different physical backgrounds. This allows a more direct and intuitive evaluation of energy storages tested in a specific application. This paper focuses on the experimental validation of energy storages (ultra-capacitor, li-ion battery, lead-acid battery and fly-wheel) to be uniformly described in one general model. A simple and budget friendly experimental setup to test the storages is designed.

Keywords: Energy storage; Li-ion battery; Lead-acid battery; Double-layer capacitor; Flywheel; Equivalent circuits.

Abbreviations

ESS energy storage system

Email addresses: ctpham@kth.se (Cong-Toan Pham, Daniel Månsson),
manssond@kth.se (Cong-Toan Pham, Daniel Månsson)

URL: <https://www.kth.se/profile/ctpham/> (Cong-Toan Pham, Daniel Månsson)

PHS pumped-hydro storage
DLC double-layer capacitor
BESS battery energy storage system
CAES compressed-air energy storage
FES flywheel energy storage
SMES superconducting magnetic energy storage
ECM equivalent circuit modeling
OCV open-circuit voltage
SoC state-of-charge
SoH state-of-health
PSU power supply unit
PWM pulse-width modulation
HPPC hybrid pulse power characterization
EMF electromotive force

1. Introduction

Since the expansion of renewable electricity generation the interest in power and energy management with energy storage systems (ESSs) has continuously increased. So far pumped-hydro storage (PHS) saturate the storage sector in terms of installed electrical capacity ($\approx 140,000\text{MWh}$) compared to the non-hydro storages ($\approx 976\text{MWh}$) [1]. However, PHS only fulfill their role as bulk storages for balancing energy in large quantities with long storage durations (e.g., peak-shaving and capacity firming) and cannot cover all fields of necessary applications [2]. Especially, the wide distribution of renewable energy sources in the electrical grid also demands for localized energy management, where feasible PHS solutions diminish. This requires other storage technologies, e.g., battery energy storage system (BESS), double-layer capacitor (DLC), flywheel energy storage (FES) etc., to take over and fill in specific applications such as power quality and voltage support [2] [3].

In 2017 the European parliament highlighted the relevance and current shortcomings of ESS in their report [4], where among others stronger considerations of ESS in the system planning process is desired. With the variety of available storage technologies the appropriate choice of ESSs for selected applications is essential to find the optimal matchings [2], [5]. In [2] and [6] a detailed description of the current existing technologies and storage applications is provided. Furthermore, they pair possible combinations and uses based on a literature survey. The ESS can further be categorized and evaluated by their technical, economical and environmental aspects as suggested in [5], [7], [8]. However, the technical suitability is the first aspect to consider for satisfactory operation. This also depends on the time period of operation, where for example flywheel are known to feature high self-discharge losses [9], [10] over long storage durations (several days). Thus, in current condition FES are best suited for direct uptake and release rather than storing over longer periods of time [2], [10]. Accurate modeling and simulation work have been highly appreciated to understand and predict storage's behavior under changing demands. Especially in the battery field the research has dedicated significant effort in capturing the battery's dynamics in equivalent electrical circuit models [11], [12], [13]. The equivalent circuit modeling (ECM) is a well-known approach and can easily be extended to other systems due to the similarity of governing relations between physical systems [14], [15]. This concept has been used to unify different ESS in one model, which describes the main dynamic features as circuit elements (R , L , C) [16]. The accuracy of models in general heavily depend on the amount and parameterization of the circuit components. A higher number of circuit elements can describe more complex dynamics, but, in cost of higher computational effort. However, the quality of the results produced by simulation work is nevertheless limited without experimental validation.

In our studies the overall goal is to introduce ECM of various ESS as means to analyze storages under selected applications, rate their performance based on their technical characteristics and introduce the ECM to planning process of ESS design. With that in mind this paper focuses on the experimental validation of the circuit models proposed in [16]. A simple low-budget experimental setup to charge and discharge ESS at specified conditions is designed. The proposed setup is able to sufficiently reproduce the results obtained through the simulation work and confirms the validity of the suggested general energy storage model in [16]. In the following sections we will first briefly summarize the general storage model from [16] (section

Figure 1: Equivalent electrical circuit model for energy storages. Here, only the battery model considers additional RC-branches. In case of a purely kinetic energy storage the voltage-controlled voltage source v_{pot} is neglected. For battery systems V_b changes with its SoC. In PHS it represents the pressure gain due to elevation and is assumed constant [16]. Further parameter descriptions for the investigated storages are explained in the corresponding sections 4.1, 4.2, 4.3, 4.4 and Appendix A & Appendix B.

2) and then describe the concept and structure of the experimental setup (section 3). In section 4 we will compare and discuss the quality of the simulated and experimental results. Here, Matlab [17] is used as the simulation software.

2. Energy storages as equivalent electrical circuits

In [14] Wellstead points out the analogy between physical quantities (mechanical, electrical, thermal, etc.) and describes their properties in terms of lumped circuit elements similar to ECM. The concept of how energy and power are related in physical systems is the same (e.g., $p_{el} = V^* I$, $p_{mech} = F^* v$, $p_{fluid} = P^* Q$). Additionally, the qualities of the respective storage remain within the circuit element, i.e., for example friction, body mass and spring coefficient are equivalent to electrical resistance, inductance and capacitance [16]. We make use of that fact to model various ESS, though different in physical nature, as one "general" electrical circuit model [16].

Fig. 1 shows the ECM concept for one energy storage unit. The circuit itself divides into a kinetic (left) and a potential (right) storage part. Both

parts address the attributes of the storage in question, where energy is either stored as potential (voltage, pressure, force, etc.) or kinetic energy (current, flow rate, velocity, etc.). For instance, BESS, PHS, DLC and compressed-air energy storage (CAES) belong to the class of potential storages, whereas FES and superconducting magnetic energy storage (SMES) maintain energy through kinetic work. Some circuit elements can be omitted if their influence on the system's dynamic behavior is negligible. This varies from case to case, e.g., the inductive load (L) in BESS and DLC is a result of parasitic inductance and can be neglected if the connection paths are shortened and optimally placed. This way the circuitry reduces to the potential storage part only (right). The DLC circuit includes an internal resistance and the capacitive branch, which symbolizes the storage capacity (C_1) and its self-discharge route ($R_{p,1}$). For the BESS, however, this RC-branch only symbolizes mass transfer limitations due to diffusion processes within the battery cells [18]. For even higher accuracy and more detailed time domain behavior the circuit can be expanded with additional branches if needed [19]. Here, two RC-branches are considered for the tested batteries and only one for the capacitor. The open-circuit voltage (OCV), here V_b , represents the charge capacity which changes with its state-of-charge (SoC). Additionally, in this paper we investigate a short time-frame (several minutes), where it is safe to neglect self-discharge effects of the batteries [18]. For kinetic storages such as FES and SMES the series RL circuit representation is valid (left in fig. 1). In a SMES electricity is stored in form of a magnetic field induced by the circulating current. The energy content then directly relates to the self-inductance L of the coil [20]. Similarly, FES can also be represented by the series RL circuit, where L translates to the moment of inertia of the rotating mass [5]. In this study we will refer all components as electrical circuit elements (R, L, C). With different variants of ECM from figure 1 we solve the following expressions for the potential, kinetic and combination of both storage parts [21] (shown for one RC-branch).

$$v''_{c,1}(t) = - \left(\frac{R_s}{L} + \frac{1}{R_{p,1}C} \right) v'_{c,1}(t) - \frac{R_s + R_{p,1}}{LCR_{p,1}} v_{c,1}(t) + \frac{v_{st} - V_m - V_b}{LC} \quad (1)$$

$$i_{kin}(t) = Cv'_{c,1}(t) + \frac{v_{c,1}(t)}{R_{p,1}} \quad (2)$$

Figure 2: Equivalent electrical circuit model for a flywheel energy storage system including the DC motor drive. R_a and L_a represent the motor's armature-winding resistance and inductance. The voltage-torque transformation is expressed as current-controlled voltage sources with the torque constant k_t as the gain factor. Bearing losses and air drag are included as V_m and R_s , which changes with rotational speed Appendix B.

If the inductive part is negligible for a potential storage system (1) reduces to (3) (individual potential storage).

$$v'_{c,i}(t) = -\frac{v_c(t)}{R_{p,i}C_i} + \frac{I_{kin}}{C_i} \quad (3)$$

In a kinetic storage the potential storage part is omitted (marked orange in 3). In case of a flywheel storage electric power needs to be converted into mechanical motion by the use of a motor. The torque produced by the motor accelerates the connected rotor mass and is, in our case, expressed as the input voltage (v_{st}). How much torque is applied depends on the motor characteristics and relates to the torque constant k_t ($\tau = k_t * i_a$) [22]. In reverse a rotating rotor shaft induces a back EMF, which also relates the angular velocity (here, $\omega = i_{kin}$) linearly to the EMF through the back emf constant k_v [22]. Both k_t and k_v are numerical equal and can here be used interchangeably [22]. In addition to the kinetic storage part we add the motor circuitry. In this paper a 24V DC motor is used to operate a small flywheel. Including the motor circuitry the following system of equations represent the storage's dynamics.

$$\begin{aligned}
i'_a(t) &= \frac{V_{in}}{L_a} - \frac{R_a}{L_a}i_a(t) - \frac{k_t}{L_a}i_{kin}(t) \\
i'_{kin}(t) &= \frac{k_t}{L}i_a(t) - \frac{R_s}{L}i_{kin}(t) - \frac{v_m}{L}
\end{aligned} \tag{4}$$

3. Experimental setup

In this chapter we will discuss the overall schematic of the low-budget setup to test different energy storages. The main objective is to charge and discharge the connected ESS with a given reference load. The maximum power rating of the implemented setup is 600W¹ (12V, 50A). The circuitry is a slightly modified version of a DC-DC step-down converter, which allows free control over constant voltage (0-12V), current (0-50A) and power charging. In this paper, we use a single conventional ATX power supply unit (PSU) to provide high power with low voltage rating, sufficient for testing single small storage units. The control system consists of a programmable microcontroller (Arduino Mega2560), which controls the operation condition of the setup.

The test setup is divided into the charging circuit (a) and the discharging circuit (b) as presented in figure 3. During charging the PSU supplies constant 12V with currents up to 50A. The amount of current drawn is regulated through the MOSFET $Q1$. The MOSFET receives a pulse-width modulation (PWM) signal (see figure at (1)) from the control circuit, which adjusts the PWM according to the requested input. An inductance L_1 ($\approx 250\mu\text{H}$) is installed to reduce the necessary switching frequency of the MOSFET. While charging the energy storage acts as the energy sink. To measure the actual current a resistor R_{meas} ($\approx 10\text{m}\Omega$) is connected in series by measuring the resulting voltage drop of the passing current. A voltage probe at node b perceives the voltage, and indirectly the corresponding current ($i_{meas} = v_{meas}/R_{meas}$). The discharge circuit operates similarly, but instead the ESS now operates as the supply. A resistance R_{load} represents the "load" with an equally small resistance of $10\text{m}\Omega$, but can be easily replaced if different loads should be simulated.

Manipulating the incoming current, voltage or power requires a feedback signal to adequately control the switching sequence of the MOSFETs. To

¹thus, non-linearity due to voltage level is not represented

Figure 3: Equivalent circuit diagram of the experimental setup. a) charging circuit b) discharging circuit. Q_1 and Q_2 are the MOSFETs used for switching and regulating the voltage or incoming current and power.

Figure 4: Open-loop control circuit with an Arduino Mega2560 microcontroller (here current control). The microcontroller sends out a reference value as a 0-5V PWM signal and is filtered through a low-pass filter to generate a smooth DC voltage output. The op-amps operate as comparators, which compare the reference value with the actual voltage from the connected nodes (b) and (c). The produced PWM signal is then passed to the MOSFETs for switching.

do that a comparator (UA741CP) is used to compare the measured signal (voltage over R_{meas}) with a reference value from the microcontroller (fig. 4). The reference value corresponds to a desired voltage to which the op-amp will adjust its output. For example, if we want to charge 10A into the storage the corresponding voltage over R_{meas} is 0.1V, or 1V after x10 gain (node b) (see fig. 4). To match this the microcontroller outputs 1V from the digital I/O. The PWM is rectified through a low-pass filter to achieve a smooth voltage output (V_+) and is then compared with the measured value (V_-) at the comparator. If $V_+ > V_-$ the MOSFET closes and conducts, and if $V_+ < V_-$ the MOSFET opens and stops further charging. This way the current is kept around the desired current value. Fig. 4 demonstrate the example for a current controlled setup. If we want to regulate the voltage or power the input values (c) and (b) should be replaced with the corresponding voltage values, i.e., the voltage difference from the nodes (a) & (b) or (c) & (d). Additionally, for power control the microcontroller reads the voltage status through an instrumentation amplifier (INA128) to compute the necessary current input ($p_{ref}/v_{st} = i_{ref}$). Figure 5 shows the picture of the experimental setup.

Figure 5: Experimental setup.

4. Model validation

In this chapter the proposed energy storage model is validated with the data obtained through the experimental setup. A lead-acid battery (6V, 12Ah), a li-ion battery (7.4V, 4.6Ah), a DLC (2.3V, 50F) and a FES ($2.632 \times 10^{-4} \text{kgm}^2$). The circuit parameters for the tested energy storage have been collected from data sheets or theoretically estimated when information is lacking.

4.1. Double-layer capacitor model validation

DLCs count as electrochemical energy storages, where the usual solid dielectric material in capacitors is replaced by a electrolyte causing an additional layer of polarized charges to form at the vicinity of the electrodes [23], [24]. This second layer (Helmholtz double-layer model) increases the charge capacity of the DLC, i.e., significant rise in capacitance, but also introduces diffusion processes during the formation of the layer [24], [25]. Kang et al. have developed a detailed ECM for DLC, including the frequency dependencies and non-linearity of the circuit parameters, where a pure capacitor can only partly represent the DLC's dynamic behavior. However, to achieve this grade of complexity detailed information regarding the materials and design is necessary. Since our main goal is to apply ECM of ESS for mid- to long-term energy management applications at fairly low frequencies ($<0.1\text{Hz}$) an ideal representation of the double-layer as a parallel $R_p C$ -branch is an acceptable approximation [24]. Note, the model used in this paper does not present the state-of-the-art, but it summarizes the basic storage dynamics useful for analyzing macroscopic system applications. The DLC (EECHW0D506 [26]) used here features 50F nominal capacitance and 2.3V rated voltage. However, the data-sheet further specifies that the capacitance can vary within a range between 30% of its nominal value, so that not all components necessarily exhibit equal behavior.

From Fig. 1 we associate the DLC to the potential storage model with a series resistance R_s and one $R_p C$ -branch. The corresponding expression is summarized in expression (3), where R_p and C determine the dynamic characteristics. Here, the circuit elements are assumed constant over the whole charging and discharging process, i.e., $\frac{dR_p}{dt} = 0$. The circuit parameters are estimated through experiments, where the internal resistance R_s is associated with the instantaneous voltage change due to sudden current

excitation. R_p can easily be determined through the time-constant of the DLC's self-discharge characteristics [16].

Figure 6 shows the charging and discharging characteristics of the DLC under changing power demand. The motivation to consider varying power demand is to emulate a prosumer profile, observe the storage's behavior and evaluate if the storage can comply with the requested power. In [21] this approach is used to analyze the storage's suitability to follow a power profile and size the system appropriately. The circuit representation is sufficient to model the real DLC and shows minor deviations as can be seen in fig. 6 a). The voltage development overall matches between experiment and simulation, but starts to deviate slightly in the discharging phase. The real capacitors discharge faster (≈ 380 s) and empty before the simulation expects it to be (≈ 360 s). The difference increases the closer the storage reaches its endpoint. However, the discharge curve shapes themselves behave similarly, which indicates that the model itself is sufficient. The overall error lies within $\pm 5\%$ except at complete discharge where the error spikes up to 20%. A possible explanation for the discrepancy lies in the underestimation of the non-linearity of the capacitance. A similar study has been conducted in [27], where a linear capacitance and constant capacitance model are contrasted. One of their findings is that assuming a constant capacitance results in the similar error when compared to measured data.

4.2. Li-Ion model validation

In the area of lithium-ion batteries the ECM modeling approach is widely accepted and has constantly been developed for greater accuracy. Especially, the modeling of the electrochemical processes is complex and involves non-linear characteristics, i.e., also non-linear circuit parameters [11], [12]. How the battery performs greatly depends on the operating condition (temperature, state-of-charge, discharge rate, frequency etc.) [18]. Hence, gathering the necessary information to cover all factors and translating the dynamic behavior to an ECM still occupies the current research interest. However, the increasing complexity to reach higher precision also goes hand in hand with experimental and computational effort. Due to this trade-off the purpose and the corresponding model has to be well defined.

Similarly to DLC our main focus is evaluating ESS for long-term load management, where some model simplifications are acceptable and still yield sufficient results. Here, the model is simplified to the circuit presented in fig. 1 (red marked area). The circuit parameters R_s , $R_{p,1}$, C_1 , $R_{p,2}$, C_2 and V_b

Figure 6: Dynamic charge and discharge with varying power of a 2x2 DLC pack (experiment vs. simulation). *a)* Capacitor pack voltage. *b)* storage input current. *c)* storage input power. *d)* relative error between experiment and simulation. DLC parameters: $R_s = 0.014\Omega$, $C = 50\text{F}$, $R_p = 227.4\Omega$.

have been estimated by an HPPC test for charge, discharge and idle-mode (Appendix A) through an optimization routine in Matlab. Note, further temperature dependent tests have not been conducted as sufficient cooling² was available to maintain a constant temperature throughout the experiments. Additionally, the state-of-health (SoH) for all batteries is assumed to be 100% as they have been newly obtained. With known discharge steps the parameters are associated to each discharge step and the corresponding SoC (see fig. A.11) [19], [28]. Within one SoC step the parameters are assumed constant between two points. The same principle has been applied for the charging state to determine the parameters while charging for each SoC step. The comparison between simulation and experiment are shown in fig. 7.

The results indicate that the experiment design is sufficient to replicate the requested input in terms of power and current (fig. 7 c)). The battery's dynamics are reflected by the terminal voltage v_{st} (fig. 7 a)), where a satisfactory match is achieved. The accuracy of estimating the parameters determines the deviation between the simulated and real voltage profile. However, a slight deviation still remains due to our simplified model, where not all dynamic responses are captured. The relative error in average stays below 1%. Visible spikes in the magnitude of the error occur but can be traced back to induced transients from the switching of the experimental setup itself (best seen at time 480s in fig. 7).

4.3. Lead-acid model validation

The lead-acid battery's dynamics can be equally reproduced by ECM [29]. In this case, the only difference to li-ion battery appears in the circuit parameters itself. Here, the circuit parameters are likewise obtained through the HPPC dataset (see A.15).

As seen in the plot 8 some discrepancy between simulation and experiment is visible. The battery's behavior also varies to its operating condition whether it is charging or discharging. Due to the high variability only a fair amount of approximation of the battery's dynamics as an ECM is achievable. For higher validity the parameterization of the ECM can be either expanded by testing multiple operation conditions or by including physico-chemical submodels [29]. Entering the microscopic scale, however, further complicates the model and the acquisition of necessary information to describe it. The

²Here, fans were used for cooling.

Figure 7: Dynamic charge and discharge with varying power of a 2x2 li-ion battery pack (experiment vs. simulation). The red curve represents the experimental data. The blue curve displays the simulation results with equal inputs. *a)* Measured and simulated li-Ion terminal voltage. *b)* Storage input current. *c)* Storage input power. *d)* Relative error between experiment and simulation. Li-Ion battery mean parameters at 20 °C and 100% SoH between 90-100% SoC from A.13: $R_s = 0.113\Omega$, $C_1 = 1027F$, $R_1 = 0.041\Omega$, $C_2 = 58880F$, $R_2 = 0.019\Omega$.

features of one specific battery are transferable, but not necessarily the estimated values and details. Especially, in respect to our goal a too complex model opposes the idea of a general modeling concept for system planning. Nevertheless, with the modest model approach and parameterization the relative error largely remains within the 1% error margin. Again, two voltage spikes are visible at the moment of switching directly between charge and discharge mode due to a poor design to mitigate occurring transients.

4.4. Flywheel storage model validation

The most common known kinetic energy storage is the flywheel. Already centuries ago the principle of conserving energy in form of rotational movement of a mass has been harnessed in order to aid the craftsmen in their work. One of the famous examples are the spindle wheel and mills [30]. This concept hasn't changed until today. But, significant improvements in FES design and material have allowed a broader adaptation of the technology. Nowadays, FES found their way in the transportation area and electrical grid, where they mainly take a supportive role in maintaining power quality, namely frequency regulation and voltage control [2], [3]. Due to their characteristics of high power density, cyclic capability and efficiency, but low storage duration they fulfill a niche when other storage technologies lack in performance. An often mentioned example is regenerative braking in vehicles, where kinetic energy is converted back into electricity. With high power peaks during braking battery-only solutions suffer setbacks due to their low power densities. Flywheels can absorb the high power and in exchange release some burden to the battery [30].

In terms of modeling a FES resembles a RL-circuit, where L symbolizes the moment of inertia and R_s the friction losses. Since the rotor shaft needs to be stabilized torque losses due to the bearings are inevitable (V_m). With this the model can be summarized as only the kinetic part of the circuit model without v_{pot} shown in figure 3. In this setup we constructed a simple flywheel device mounted on a DC motor. The device pales in comparison to modern dedicated flywheel storage devices, but is sufficient in our case (see 9). The DC motor serves as the power transformation system and also affects the total dynamics of the system.

The flywheel used in this paper consists of a 0.29kg thin, solid steel disc with 4.25cm radius. The rotational speed of the rotor is measured by a tachometer. Figure 10 visualizes the differences between the experimental and simulation results. The relevant information to take out is how the

Figure 8: Dynamic charge and discharge with varying power of a Lead-acid battery (experiment vs. simulation). The red curve shows the experimental data. The blue curve displays the simulation results with equal inputs. *a)* Measured and simulated lead-acid battery terminal voltage. *b)* Storage input current. *c)* Comparison of the storage input power. *d)* Relative error between experiment and simulation. Lead-acid battery mean parameters at 20 °C and 100% SoH between 70-80% SoC from A.18: $R_s = 0.018\Omega$, $C_1 = 558F$, $R_1 = 0.063\Omega$, $C_2 = 32586F$, $R_2 = 0.072\Omega$.

Figure 9: Flywheel storage setup with self-build tachometer measurement.

Figure 10: Dynamic charge with varying power input of a flywheel energy storage (experiment vs. simulation). The red curve shows the obtained data from the experiment. The blue curve represents the simulated results with equal inputs. *a)* Motor terminal voltage. *b)* Measured and simulated angular velocity of the flywheel mass. *c)* Storage input power. *d)* Relative error between experiment and simulation. Motor parameters: armature resistance $R_a = 7.9\Omega$, armature winding $L_a = 0.77\text{mH}$, $k_t = 0.0255\text{Nm/A}$. Flywheel parameters: rotor mass $m = 0.29\text{kg}$, moment of inertia $L = 2.632 \times 10^{-4}\text{kgm}^2$, max. energy stored $W_{kin} = 53.4\text{J}$. The friction losses vary with rotational speed; the estimation calculation are listed in Appendix B.

angular speed of the flywheel rotor develops with changing inputs and while self-discharging. Some deviation is observable in fig. 10 b) at the start of the charging process and from the minor difference in input voltage in 10 a). The voltage spike only occurs at the start due the high power consumption during the ramp-up process of electric motors, which is not represented in the simple motor model. This explains the speed deviation and the resulting high error rate. This error quickly decays and settles within a 5% margin in average over the remaining period. The remaining residues then trace back to the inaccuracies in the parametrization of the circuit elements. Apart the given motor parameters the main unknown variable are the friction losses, which vary with rotation speed. The corresponding calculations and assumptions made are listed in the Appendix B. Overall, the profiles matches satisfactorily and validates the ECM approach for non-electrical systems as well.

4.5. *Discussion*

The foregoing sections have shown the adequacy of the simplified models to represent basic dynamic behavior of the respective storages. However, visible deviations between simulated and experimental results remain and indicate to an incomplete model or insufficient setup design. In this case differences are to be expected in the light of using simplified storage models, but also in how accurate the parameter estimation is. Nevertheless, to address the occurring errors some measurements can be taken. Electrochemical storages are sensitive to their operation condition and the environment they are placed in. In this paper, the parameter estimation for batteries covered a small portion of the operation range. The results can be improved if a wider range of currents and temperature dependencies is considered. The same is true for DLCs, where in this case all parameters are assumed constant. The error can be further mitigated if we allow parameter variation since DLC feature some electrochemical properties. The flywheel here is a representation in the simplest form. To decrease the error the flywheel design itself requires additional attention. The absence of housing prevents a controlled environment for estimating the air drag losses. Additionally, the flywheel rotor requires improved stability as vibrations further enhance losses, which are not captured in this model. A second contributing factor is the electrical setup (cables, mosfets, control circuitry etc.). Unwanted switching noise and other electromagnetic interferences can distort the measured profile. A filter and appropriate shielding are simple solutions to mitigate this problem.

To restate the purpose, the ECM has been deliberately chosen as a modeling tool since its universality for also non-electrical systems [5]. The ECM also allows for an improved analysis and understanding of ESS under varying operation condition. This has been implemented in [16] as a means to simulate and evaluate ESS for a specific grid application. Furthermore, the results also provide valuable information on performance such as cyclic efficiency, performed cycles, minimum required capacity and power rating to outline the appropriate storage size. The models here do not present the state-of-the-art of current achievements in the modeling field but this paper should be regarded as bridge to utilize and introduce the ECM to the design and planning stage of ESS.

5. Conclusion

This study concentrates on the validation of the general ECM concept for a variety of energy storages. A budget friendly test setup has been designed to test and operate the small scale ESS with varying power input. The showcased results here only represent a small portion of available ESS. However, the concept in its core is applicable to all ESS, where differences depend on the parameterization of the circuit elements. Obtaining the fitting parameter values and dependencies is not trivial and grows more laborious with higher required model accuracy. The models used here are modest and capture the main, but not all, dynamic features of the respective storages. The advantage of ECM is the modularity, which, importantly, can be freely adjusted to a desired level. In our case, we aim to keep the model as simple as possible and as accurate as needed to maintain the universality. Due to the physical modeling behind the ECM, this allows the concept to be extended to other existing or newly developed storage types to be easily analyzed and evaluated for any application purpose.

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Figure A.11: HPPC test of the 2x2 Li-Ion battery pack (Sanyo UR18650) to determine discharging parameters. *a)* Terminal voltage. The red curve is the optimized curve for the ECM. *b)* Discharge current pulse.

Appendix A. Hybrid pulse power characterization data curve

Figure A.11 displays the hybrid pulse power characterization (HPPC) curve for the li-ion battery pack (Sanyo UR18650 [31]). The corresponding estimated parameters follow in figure A.11 and A.12 for the respective operation mode. Using the relaxation time in either the charge or the discharge profile provides the parameters when the storage is idle. The corresponding parameters for the li-ion battery are plotted in figure A.13 and A.14.

The following figures (A.15, A.16) show the measured data for the lead-acid battery (LC-P0612P [32]).

Appendix B. Flywheel energy storage parameter estimation

Most of the FES components can be assumed constant except for the losses. The losses are mainly associated with different friction losses of the rotating elements with its surrounding media. In our case, the flywheel disc rotates in air, where drag losses R_s occur at the surface layer. Another losses

Figure A.12: HPPC test of the 2x2 Li-Ion battery pack (Sanyo UR18650) to determine charging parameters. *a)* Terminal voltage. The red curve is the optimized curve for the ECM. *b)* Charge current pulse.

Figure A.13: Estimated li-ion battery (Sanyo UR18650) parameters for different operating conditions and SoC: *a*) charge, *b*) discharge and *c*) idle (from A.11, A.12).

Figure A.14: Open-circuit voltage over the state-of-charge of the li-ion battery pack (Sanyo UR18650).

occur due to bearing connections V_m (3). The estimation of drag and bearing losses are calculated according to [30] and [33].

Appendix B.1. Drag losses in air

The aerodynamic drag depends on the rotational speed of the flywheel. The estimation of the torque losses heavily vary with the grade of turbulence near the surface area [30]. The loss term R_s is calculated through the following expressions. It should be noted that the transition between laminar and turbulent flow ($\approx 5 \times 10^4$) is a complicated region, where both states of flow can exist and accurate loss estimation are difficult to obtain. Here, out of simplicity we assume a sharp transition from laminar to turbulent flow at the threshold value. The following expressions are only valid in air and without rotor housing [30].

$$M_{air} = \rho_{air} \omega^2 r_{fes}^5 C_m = R_s(\omega) \omega \quad (B.1)$$

$$R_s = \rho_{air} \omega r_{fes}^5 C_m \quad (B.2)$$

Figure A.15: HPPC test of the lead-acid battery (LC-P0612P) to determine discharging parameters. *a)* Terminal voltage. The red curve is the optimized curve for the ECM. *b)* Discharge current pulse.

Figure A.16: HPPC test of the lead-acid battery (LC-P0612P) to determine charging parameters. *a)* Terminal voltage to determine discharging parameters. The red curve is the optimized curve for the ECM. *b)* Charge current pulse.

Figure A.17: Open-circuit voltage over the state-of-charge of the lead-acid battery (LC-P0612P).

$$C_m = \begin{cases} 3.87Re^{-0.5} & \text{laminar flow, } Re < 5 \times 10^4 \\ 0.146Re^{-1/5} & \text{turbulent flow, } Re \geq 5 \times 10^4 \end{cases} \quad (\text{B.3})$$

$$Re = \frac{\rho_{air} r_{fes}^2 \omega}{\eta_{air}} \quad (\text{B.4})$$

M_{air}	air drag moment losses
ρ_{air}	air density [kg/m ³]
r_{fes}	flywheel rotor outer radius [m]
ω	angular velocity [rad/s]
η_{air}	air dynamic viscosity [Pa · s]

Appendix B.2. Bearing losses

The bearing moment losses $M_{bearing}$ are represented as V_m in our ECM. The total losses relate to rolling friction M_{rr} , sliding friction M_{sl} , bearing seal friction M_{seals} and lubricant drag M_{drag} . However, in this study the seal frictions and lubricant drag losses are neglected as both are seldom used in

Figure A.18: Estimated lead-acid battery (LC-P0612P) parameters for different operating conditions and SoC: a) charge, b) discharge and c) idle (from A.15, A.16).

small DC motors as in our example. SKF calculates the drag losses according to bearings partially or fully submerged in oil baths, which is not the case here [33]. Therefore, we only consider rolling and friction loss terms. Note, the assumptions here base on the information provided by the manufacturer's data sheet (DC motor A-Max 26 110940 [34]). According to SKF the friction values also depend on how lubrication/grease is applied and can vary by several factors of the calculated frictions itself [33]. In our case, a factor c_f^3 of 5 yielded satisfactory results.

$$V_m = M_{bearing} = (M_{rr} + M_{sl}) \times c_f \quad (\text{B.5})$$

$$M_{rr} = \phi_{ish}\phi_{rs}G_{rr}(\nu n)^{0.6} \quad (\text{B.6})$$

$$G_{rr} = R_1 d_m^{1.97} [F_r + F_{g,rs} + R_2 F_a]^{0.54} \quad (\text{B.7})$$

$$F_{g,rs} = R_3 d_m^4 n^2 \quad (\text{B.8})$$

$$\phi_{ish} = \frac{1}{1 + 1.84 \times 10^{-9} (n d_m)^{1.28} \nu^{0.64}} \quad (\text{B.9})$$

$$\phi_{rs} = \frac{1}{e^{K_{rs}\nu n(d+D)} \sqrt{\frac{K_z}{2(D-d)}}} \quad (\text{B.10})$$

$$M_{sl} = G_{sl}\mu_{sl} \quad (\text{B.11})$$

$$G_{sl} = S_1 d_m^{0.26} \left[(F_r + F_{g,sl})^{4/3} + S_2 F_a^{4/3} \right] \quad (\text{B.12})$$

$$F_{g,sl} = S_3 d_m^4 n^2 \quad (\text{B.13})$$

³Here, iteratively estimated.

M_{rr}	rolling friction moment losses
M_{sl}	sliding friction moment losses
ϕ_{ish}	inlet shear heating reduction factor
ϕ_{rs}	kinematic replenishment reduction factor
G_{rr}	bearing type dependent variable (ball bearing)
ν	viscosity of lubricant [mm ² /s]
n	rotational speed [rpm]
R_1, R_2, R_3	geometric constants for rolling friction losses single row angular contact ball bearing
F_r	radial load [N]
F_a	axial load [N]
d	bearing bore diameter (3mm) [mm]
D	bearing outside diameter (10mm) [mm]
d_m	bearing mean diameter (6.5mm) [mm]
K_{rs}	replenishment constant for grease (6×10^{-8})
K_z	bearing type related geometric constant 4.4 for single row angular contact ball bearing
G_{sl}	bearing type dependent variable (ball bearing)
S_1, S_2, S_3	geometric constants for sliding friction losses single row angular contact ball bearing
μ_{sl}	sliding friction coefficient (0.6 for steel)
c_f	correction factor dependent on lubrication/grease fill