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# Management of a free-floating electrical scooters fleet

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**Résumé**—Les scooters électriques en accès libre sont devenues des acteurs majeurs du transport sur de courtes distances. La raison de leur succès réside dans le gain de temps et la liberté que procurent ces véhicules en libre-service. La batterie Lithium Ion est un élément clé qui représente environ un tiers du coût total de l'appareil et affecte ses performances globales [2].

Le but de ce travail a été de développer un modèle de batterie applicable à la gestion d'une flotte de scooters électriques en libre-service. L'utilisation quotidienne aléatoire de la flotte a été simulée par processus de Markov. La batterie a été modélisée avec Modelica, un langage particulièrement adapté à la conception de modèles 0D/1D par l'utilisation d'équations différentielles.

La validation du modèle a été effectuée sur les données de Battery NASA Prognostic Dataset [5], un jeu de données largement utilisé dans de nombreuses publications scientifiques [6], [7].

**Abstract**—Free-floating electrical scooters (ES) have become major players in short-distance transportation. The reason for their success lies in the time saving and the freedom given by the self-service vehicles. Their key element is the Lithium Ion battery, which affects the overall performance and account for about one-third of the total ES cost [2].

The scope of this work has been to develop a battery model to be applied to the case of the management of an e-scooter free-floating fleet. Random daily usage of the fleet has been simulated by the use of Markov processes, while the battery has been modeled with Modelica, a language particularly suited for designing 0D/1D models by use of differential equations.

The validation of the model has been performed with respect to the Battery NASA Prognostic Dataset [5], which has been extensively used in many scientific publications [6], [7].

**Keywords**—Battery, Longevity, State of Charge, State of Health, E-Scooters

## I. INTRODUCTION

Micro mobility spreads rapidly over the course of the last four years. Since their launch in 2018, the companies of shared electric scooters (ES) and e-bikes have increased the number of vehicles available in the big cities, following the growing demand from users. In Europe, Paris has been among the promoters of sharing services, first with the Velib

company, which in 2007 launched its (non-electrical) bikes fleet with 7000 bikes and 750 stations, then with different private companies such as TIER, Lime, and others. The city currently offers different experiences, such as docked and free-floating fleets of e-bikes and e-scooters with different price plans and strategies.

E-scooters and e-bikes are principally used for mid-range transportation, where the distance is too long for walking, while the usage of the cars can be inconvenient due to parking or environmental concerns. Also, the shared service allows avoiding the initial investment necessary to buy the vehicles and the worries about the parking and the possibility of it getting stolen. In particular, the free-floating fleet, without the need of a docked station in which leaving the vehicle, gave the user a great amount of freedom, even if concerns remain on the wilds parking on sidewalks.

The use of this kind of vehicle is made possible by the availability of always more efficient Lithium-ion batteries. Batteries affect the overall performance, in particular of e-scooters, which rely completely on the battery itself for their operations, while e-bikes can also work as a simple bike if the battery is discharged. The battery is also the main economical factor, accounting for about one-third of the overall e-scooter cost [2].

Lithium-Ions are the preferred solution for the e-scooters battery, given their excellent energy density and longevity with respect to other battery types. A battery pack is composed of many individual cells, which for lithium-ion (Li-Ion) are usually 18650 (18x65mm cylinder). Each of the cells has a nominal potential of 3.6V and operates between 2.5V (0% charge) to 4.2V (100% charge). Packing in series or in parallel many individual Li-Ion cells, it allows obtaining higher voltages or currents respectively. If used correctly, batteries can last hundreds of cycles due to their rechargeable nature. However, they are subject to irreversible degradation processes which can affect their performances and eventually leads to the inability to supply the necessary power. On the other side, if used improperly, the failure can be sudden, and lead to the

explosion of the battery.

In order to avoid so, every battery is equipped with a Battery Management System (BMS), which monitors that the Li-Ion batteries are working in the nominal conditions (Voltage and Temperature, etc.) and guarantee that the charging process stops when the voltage reaches 4.2V. Nonetheless, the amount of data available from the batteries allow the development of strategies for diagnostic and prognostic purposes, to further improve the safety and optimize and maximize the Remaining Useful Life (RUL) of the battery. This consequently allows to derive smarter strategies for the batteries recharge and replacement.

In this work, the battery has been modeled following [4]: the novelty of the approach lies in the usage of the Modelica language to describe the discharge behavior of the battery with both continuous or varying discharge profiles. The model has been validated with data from the NASA prognostic laboratory [5]. As described in [7], the electrochemical degradation processes happening in the battery cause a drop in the released voltage, which can be described as an increment of the internal resistance  $R_0$  and a decrease of the maximum number  $q_{max}$  of moving Lithium-Ions from the negative to the positive electrode.

The usage of an e-scooter dockless fleet has been simulated by the use of Markov processes, using transition probabilities based on the time of the day, the state of charge of the battery, and the current state of usage. The possible state has been simplified as “Run” when the scooter is used, “Sleep” when the scooter is stopped and “Charge”, meaning the scooter is brought to the recharging center. This allows obtaining a plausible random daily usage, which is used to feed the model in order to compute the e-scooter battery State of Charge, assuming for simplicity’s sake a constant discharge rate of 2A.

The interaction between the Modelica model and the random daily usage has been performed employing the Functional Mock-Up Interface (FMI), which allows utilizing the Modelica degradation model directly within a python script. This way has two great advantages: it allows the use of the Modelica language to build the model, and in the meantime it is possible to perform easily sensitivity analysis and understand the impact of controlled usage behavior, which will not be possible in a simple Modelica framework.

This paper is organized as follows. Section II describes briefly the language Modelica and the equation used to derive the Li-Ion model. In Section III it is described how the Random Daily Usage of e-scooters has been built. Results are then presented in Section IV. Lastly, Section V derives the conclusions and the future development of this work.

## II. MODELICA BATTERY MODEL

### A. Modelica

A model is a mathematical description of a system that aims to recreate its functionality in a digital framework. It recurs to a set of equations, solved in different fashions. In order to avoid the computational burden of methods such as finite elements,

0D/1D models are often used to describe systems through ordinary differential equations. Modelica is a programming language well suited for designing 0D/1D models [8]. In a Modelica framework, the model is a system of differential equations, solved by dedicated multipurpose third-party tools such as OpenModelica [9].

To calibrate the model parameters and allow interaction between the model and other programming languages, more suited for statistical analysis or uncertainties quantification, the Functional Mock-Up Interface (FMI) standard [10] has been proposed. This standard allows treating the numerical model as a black box in other language frameworks, since it consists of an XML file describing the variables of the model and a set of possible compiled functions for carrying out the simulations. Treating it as a black box, it allows using the Functional Mock-Up Unit (FMU) as a function, defining inputs, and obtaining the results of the simulation as output.

Thanks to PyFMI [11] it is possible to include the FMU in a python script, facilitating the statistical analysis as well as the tuning of the parameters to optimize the numerical model. An example of the optimization and tuning of the parameters will be given in the IV section.

### B. Lithium-Ion Batteries

Lithium-Ion Batteries are electrochemical devices able to directly store energy and release it when necessary. The main advantages of the Li-Ion with respect to other kinds of electrochemical converters lie in their rechargeable nature, without memory effect, higher energy density, and longer life cycle. Li-Ions are composed of different cells, which allows them to be packed in different configurations according to the purpose of the application. The nominal voltage of the single-cell lies between 3.6 and 3.85 V, which can be increased in the battery pack by connecting them in series or parallel to reach the necessarily required levels of voltages or currents. The most commonly used cell is the 18650 (18x65 mm cylindrical), with a nominal voltage of 3.7 V and a maximum voltage of 4.2V, which will be the scope of this work. A schematic structure of a Lithium-Ion Battery can be appreciated in Fig. 1: during discharge, the mobile Li-Ion resides in the negative electrode, and when a load is applied current is allowed to flow from the positive to the negative electrode. This results in the liberation of Li Ions and electrons, which move towards the positive electrode through the separator.

During usage, the performance of the battery degrades. The two main factors that contribute to the degradation of the battery performances are the loss of active ions and an increase in the internal battery resistance. The main processes leading to these phenomena are:

- 1) Solid Electrolyte Interface (SEI) growth: formation of a solid layer on the surface of active material, which can happen both during cycling and storage at high temperatures.
- 2) Lithium Corrosion: Lithium corrodes, leading to an irreversible loss of mobile ions.

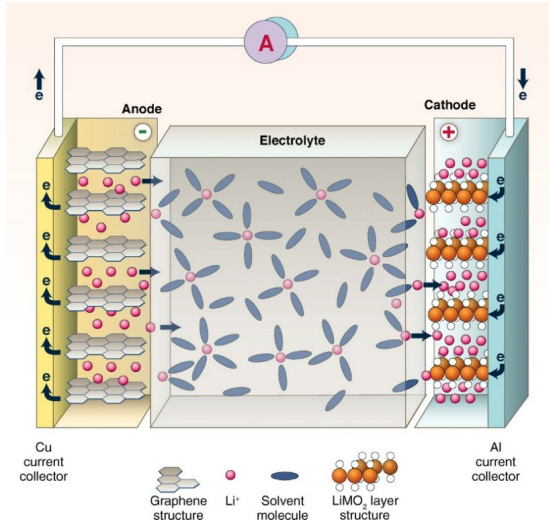


Figure 1: Schematic structure of a Lithium-Ion Battery [12]

However, the processes are usually not localized and deeply influenced by external conditions, such as temperature and usage, making the degradation of these devices difficult to comprehend and predict. Also, some phenomena, such as the capacity recovery phenomenon [13], allow the battery to recover some of the lost capacity, which also increases the difficulties in understanding the overall processes inside the batteries.

### C. Battery Model

The battery has been modeled by the use of the Modelica language. The final goal of this model is to simulate the output voltage and temperature of the cell battery, in order to compute its State of Charge (SOC). The cut-off voltage of the battery, meaning the one defining the End of Discharge (EOD) has been defined at 2.5V. The overall battery voltage  $V$  is obtained by the difference between the potential at the positive current collector and the negative current collector, minus the voltage drops caused by solid-phase ohmic resistance  $V_0$  and the surface overpotential  $V_\eta$ .

The State of Charge (SOC) of the battery is defined as:

$$SOC = \frac{q_n}{0.6q_{max}} \quad (1)$$

where  $q_n$  is the number of ions at the negative electrode, where  $q_{max}$  is the maximum available number. From  $q_i$  and  $q_{max}$  we can define the mole fraction  $x_i$ , where  $i$  can be  $n$  (negative) or  $p$  (positive), as:

$$x_i = \frac{q_i}{q_{max}} \quad (2)$$

The battery is considered fully charged when  $x_p = 0.4$ . Considering that from definition  $q_{max} = q_p + q_n$ , it follows that  $x_n + x_p = 1$ , from which the factor  $1/0.6$  of (1). On the other side, when the battery is fully discharged,  $x_n = 0$  and  $SOC = 0$ .

The main equations used to compute the temperature and the output voltage of the battery will now be reported. The

Parameter	Value
$U_{0,p}$	4.03 V
$A_{p,0}$	-33642.23 J/mol
$A_{p,1}$	0.11 J/mol
$A_{p,2}$	23506.89 J/mol
$A_{p,3}$	-74679.26 J/mol
$A_{p,4}$	14359.34 J/mol
$A_{p,5}$	307849.79 J/mol
$A_{p,6}$	85053.13 J/mol
$A_{p,7}$	-1075148.06 J/mol
$A_{p,8}$	2173.62 J/mol
$A_{p,9}$	991586.68 J/mol
$A_{p,10}$	283423.47 J/mol
$A_{p,11}$	-163020.34 J/mol
$A_{p,12}$	-470297.35 J/mol
$U_{0,n}$	0.01 V
$A_{n,0}$	86.19 J/mol

Table I: Battery Model Parameter [14].

interested reader can find a detailed description of these equations in [14].

The potential equilibrium of an electrode is described by the Nernst equation:

$$V_{U,i} = U_0 + \frac{RT}{nF} \ln \left( \frac{1 - x_i}{x_i} \right) + V_{INT,i} \quad (3)$$

where  $U_0$  is a reference potential,  $R$  is the universal gas constant,  $T$  is the Temperature of the battery,  $F$  is the Faraday constant, and  $V_{INT,i}$  the activity correction term.  $n$  indicates the number of electrons transferred in the reaction, equal to 1 in the case of Li-Ion. During discharge,  $x_p$  grows from 0.4 to 1, while  $x_n$  decreases from 0.6 to 0. This results in the decrease of  $V_{U,p} - V_{U,n}$ .

The activity coefficient  $V_{INT,i}$  is related to the Gibbs excess free energy, computed by Redlich-Kister expansion:

$$V_{INT,i} = \frac{1}{nF} \left( \sum_{k=0}^{N_i} A_{i,k} \left( (2x_i - 1)^{k+1} - \frac{2x_i k (1 - x_i)}{(2x_i - 1)^{1-k}} \right) \right) \quad (4)$$

with  $N_p = 12$  and  $N_n = 0$ . The  $A$  parameters have been listed in Table I.

The variation of the mole fractions  $x_i$ , which determine the variation of the voltages, can be derived by the following differential equation, describing how the charge moves through the electrodes. Electrodes are also divided into two volumes, bulk (subscript  $b$ ) and surface (subscript  $s$ ). This difference is important because in the electrode the reaction takes place at the surface, causing a concentration gradient between bulk

and surface. The diffusion rate from bulk to the surface can hence be described as:

$$\dot{q}_{bs,i} = \frac{1}{D}(c_{b,i} - c_{s,i}) \quad (5)$$

where  $D$  is the diffusion constant and  $c$  are the concentrations of Li-Ion at the bulk and surface of the two electrodes. The charge  $q$  variations can hence be described as:

$$\dot{q}_{s,p} = i_{app} + \dot{q}_{bs,p} \quad (6)$$

$$\dot{q}_{b,i} = -\dot{q}_{bs,i} \quad (7)$$

$$\dot{q}_{s,n} = -i_{app} + \dot{q}_{bs,n} \quad (8)$$

$i_{app}$  is the applied current. With these equations we can compute  $x_{s,i}$  and  $x_{b,i}$ , and substitute the mole fraction at the surface  $x_{s,i}$  in (3) in place of the total mole fraction. In this way, it is possible to explicitly account for the concentration overpotential at the surface layers, since the observed voltage is only dependent on surface behavior. At the end of the discharge process, the difference between bulk and surface potentials causes a redistribution of ions in the electrodes, resulting in a raising of the voltage, which can be appreciated in Fig. 4.

The output voltage drops further due to the Ohmic Overpotential  $V_0$  and the Surface Overpotential  $V_{\eta,i}$ , respectively defined as:

$$V_0 = i_{app}R_0 \quad (9)$$

$$V_{\eta,i} = \frac{RT}{F\alpha} \operatorname{arcsinh} \left( \frac{J_i}{2J_{i0}} \right) \quad (10)$$

Eq. (10) is the Butler-Volmer equation, simplified since  $\alpha$ , the symmetry factor is 0.5 for Li-Ion while  $J_i$  and  $J_{i0}$  are the current density and the exchange current density, defined as:

$$J_i = i/S_i \quad (11)$$

$$J_{i0} = k_i(1 - x_{s,i})^\alpha (x_{s,i})^{1-\alpha} \quad (12)$$

with  $k_i$  being a lumped parameter. Since the voltage drops take place at the surface level, the exchange current density is computed using  $x_{s,i}$ .

Voltage drops in the battery do not happen instantaneously, hence to take that into account we consider:

$$\dot{V}'_0 = (V_0 - V'_0)/\tau_0 \quad (13)$$

$$\dot{V}'_{\eta,i} = (V_{\eta,i} - V'_{\eta,i})/\tau_{\eta,i} \quad (14)$$

The temperature variation of the battery can be computed as:

$$\dot{T} = \frac{(V'_0 + V'_{\eta,p} + V'_{\eta,n})i_{app}}{m_c} + \frac{T_0 - T}{\tau_T} \quad (15)$$

Parameters  $\tau$  are empirical time constants to account for the transients. Having defined all the components, it is finally possible to define the output battery voltage as:

$$V = V_{U,p} - V_{U,n} - V'_0 - V'_{\eta,p} - V'_{\eta,n} \quad (16)$$

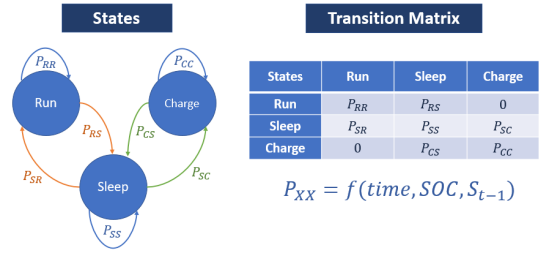


Figure 2: Concepts of the system states and associated transition matrix

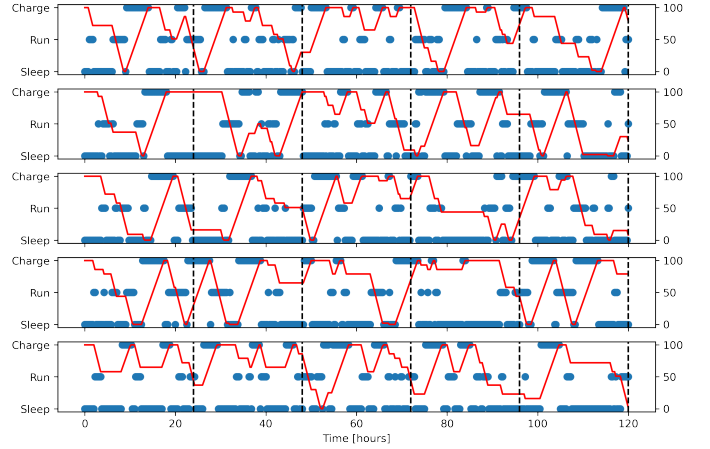


Figure 3: Simulation of random daily usage of the e-scooters.

### III. RANDOM DAILY USAGE

The random daily usage of a fleet of e-scooters has been simulated by the use of Markov processes. Markov processes are a class of stochastic processes in which the future state of a system is only dependent on the current state. It is particularly well suited for predicting behaviors within large systems, and for that reason has been used to simulate the behavior of the e-scooters fleet.

To describe the behavior, it has been assumed that the e-scooters can assume three states, meaning "Run", "Charge" and "Sleep". The states describe the condition in which the ESs are used, recharged, or in the streets waiting for being used. The laws regulating the passage between two states in a Markov process are defined by a transition matrix, which described the probability that the scooters changes or remain in their current state, illustrated in Fig. 2

The described fleet is a free-floating, meaning that the e-scooters can not be plugged into the recharging dock directly by the user, but are left directly in the street at the end of the usage. For this reason, it is not possible to pass directly from state *Run* to state *Charge* and opposite, hence the transition probabilities  $P_{RC}$  and  $P_{CR}$  are 0.

Furthermore, to simulate in a realistic possible way the usage of the ESs, the transition probabilities are dependent on other factors, such as the time of the day or the ES battery State of Charge. This is to include the dependencies of a real-life application, in which the e-scooters are more liked

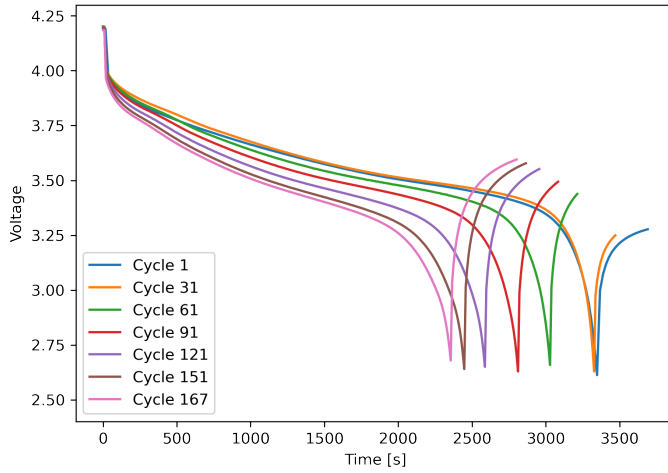


Figure 4: NASA Battery B0005 [5]

to be used during certain phases of the day, for example during the morning or afternoon commute to work, and the fact that scooters are more likely to be used when they have a sufficiently high level of SOC.

Fig. 3 shows the simulation of 5 scooters during 5 days of usage. The blue dots represent the state, while the red lines simulate the discharge/charge cycles of the batteries.

#### IV. RESULTS

The model has been calibrated based on the NASA Battery Dataset [5]. In particular, the model has been calibrated using the battery denominated *B0005*. Fig. 4 shows the behavior of the Voltage of the battery and the effect of aging on it. As described in II-B, the aging leads to the increment of  $R_0$  and a decrement of  $q_{max}$ . As a result, the voltage reaches the cut-off, 2.6V, faster, and the equilibrium voltage after the cut-off is higher.

The battery has been first calibrated by replicating the results of the battery *B0005* at its first cycle, which corresponds to 0% damage, hence a State of Health (SOH) of 100%. The main parameters used for this simulation are shown in Table II. The simulation uses a starting temperature of 24°, and a constant discharge current of 2A. When the cut-off is reached, the current is brought to zero and the voltage stabilizes at its equilibrium point. The comparison between the voltage of the two can be appreciated in Fig. 6.

On the other side, to define the SOH of 0% has been taken the last cycle of the *B0005*, meaning Cycle 167. The increase of  $R_0$  and the decreasing of  $q_{max}$  allows to tune the model in order to obtain the correct duration of the discharge, while the variation of  $D$  is the main factor in the increase of the equilibrium potential. To obtain these results, the degradation has been assumed linear for simplicity's sake, and the parameter  $R_0$  has been increased from 0.1 to 0.15 Ohm, meaning an increase of 0.25% per cycle.  $q_{max}$  decreased from 11500 C to 8250, with a decrease of 0.2% per cycle and lastly, coefficient  $D$  increased by 0.35% per cycle.

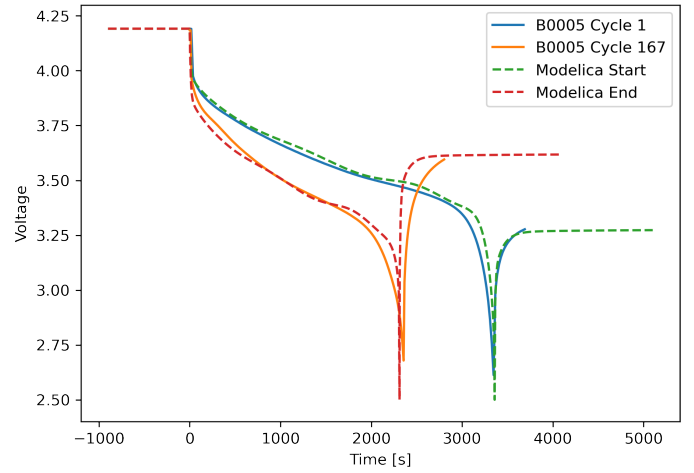


Figure 5: Comparison between Battery B0005 and the Modelica Model

Parameter	Value (SOH 100%)	Value (SOH 0%)
$q_{max}[C]$	11500	8250
$R_0[\Omega]$	0.1	0.15
$D[mols/C/m^3]$	$9 \times 10^6$	$5 \times 10^6$

Table II: Model Parameter

We present now the results obtained by the interaction between the physical model and the ESs random daily usage. The process is iterative since the daily usage depends on the State of Charge, which is computed by the model. The discharge rate of the battery is assumed constant and equal to 2A. It is worth noting that the behavior is representative of a single battery cell, and not a complete battery pack, which consist of different cell stacked together, and is able to increase the amount of working time of an e-scooter.

Fig. 6 shows the voltage behavior for a single same discharge cycle at the beginning and the end of the life of the battery. To compare them, we generate a single random usage, where the last run is performed until the batteries reach 2.5V, the End of Discharge (EOD). The effect of the degradation of the performances can be appreciated in a shorter time to reach the EOD and a generally lower output voltage throughout the overall discharge cycle.

As a consequence, as can be appreciated in Fig. 7, the SOC of the battery decreases more rapidly, with an increase in the slope between the beginning and end of life.

#### V. CONCLUSIONS

The scope of this work has been to develop a reliable model for the batteries to be applied to the case of a fleet of free-floating e-scooters. The model has been built using the Modelica language, which allows directly writing the equations, in contrast with the typical variable assignment of programming languages. In this way, it is the simulation



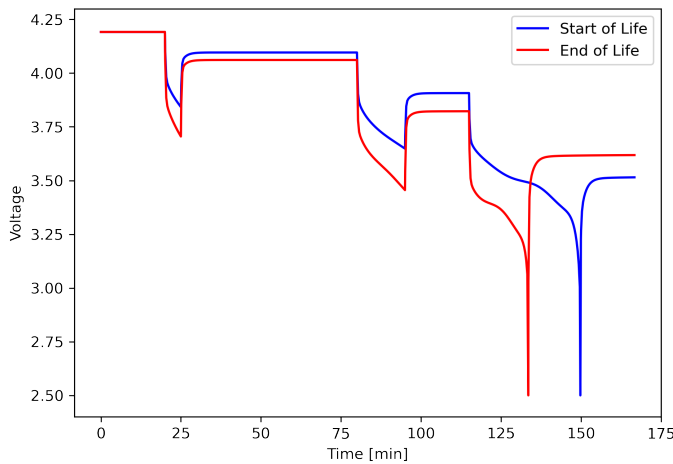


Figure 6: Comparison between same random walk with a battery at SOH 100% and a battery at the end of its lifetime

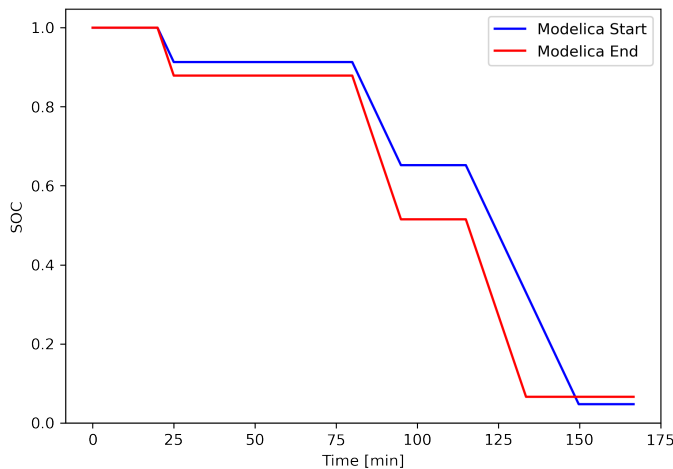


Figure 7: Comparison between SOC of same random walk with a battery at SOH 100% and a battery at the end of its lifetime

engine that takes care of manipulating the equations in order to solve them, which results in a more simple and intuitive way of defining the model. The daily usage of the e-scooter has been simulated by use of a Markov process, in which the transition matrix probabilities allow to consider various variables in their use, such as the State of Charge and the time of the day.

The interaction between Modelica and python through the use of the Functional Mock-Up Interface standard allowed us to validate the model and integrate it with the generation of daily random usage, allowing to compute the State of Charge and the degradation of the battery during the lifetime.

The calibration and validation of the model performed will allow future work to focus on more practical aspects, such as the usage of prognostics methods in order to predict the Remaining Useful Life of the battery and the associated quantification of the uncertainties. In this way will be possible to derive optimal strategies for the maintenance

and replacement of the batteries of the fleet.

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