Developing a Health-Conscious Energy Management Strategy Based on Prognostics for a Battery/Fuel Cell Hybrid Electric Vehicle

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Abstract—Since the degradation of energy sources in battery/fuel cell hybrid electric vehicles (HEVs) is inevitable and highly influences the durability of the system, an energy management strategy (EMS) aiming at prolonging the lifetime is demanding. In fact, the predictive nature of prognostics gives chance to develop such an EMS, which performs energy management through automatic corrective actions with the help of the awareness of energy sources' health states. This paper has addressed some scientific issues encountered when considering EMS based on prognostics and proposed an EMS based on fuzzy logic control which has successfully mitigated the battery degradation.

Index Terms—hybrid electric vehicle, prognostics, energy management, fuzzy logic

I. Introduction

Hybrid electric vehicles (HEVs) have generated great interests in the automotive market, where lithium-ion battery and proton exchange membrane fuel cell (PEMFC) exist to be the most favourable energy sources due to their high energy density. However, both of them may suffer from different degrees of degradation due to the ageing phenomenon during storage or under operation mode. A delicately designed energy management strategy (EMS) is demanding to improve the durability of the hybrid system.

Prognostics and health management (PHM) has existed to be a favourable discipline to assess the health state of energy sources and quantify the remaining useful life (RUL) at an early stage. Prognostics, as a key process in PHM, has been used to make predictions on battery's state of health (SOH). There are three types of prognostics methods. For example, support vector machine (SVM) [3], neural network (NN) [4] and Gaussian process [5] have been used as data-driven methods to simply capture the inherent trends of battery' ageing phenomenon, while filter algorithms like extended Kalman filter (EKF) [6], unscented Kalman filter (UKF) [7] and particle filter (PF) [8] have existed as hybrid methods to perform prognostics with state-space models. Moreover, equivalent circuit model (ECM) makes it possible to develop a model-based method which uses the knowledge of battery's physical failing mechanism to estimate the RUL [9].

Although performing prognostics on energy sources enables the fore-alarming of the products' malfunctions, from a PHM point of view, to improve the durability and to reduce cycle life cost are the final objectives to achieve. Various efforts have been made to develop the EMSs based on pre-developed degradation models, such as empirical models, semi-empirical models and electrochemical ones, which are added to the strategies to formulate a multi-objective problem. These multi-objective problems can be solved by rule-based strategies [10]–[13] or optimization-based strategies [14]–[19]. Nevertheless, these works are based on pre-developed degradation models and no prognostics work is combined to the EMS. Lack of the knowledge of the current health state, the EMS may not optimally control the HEV and consequently lead to energy waste and economic loss.

Therefore, in electric vehicle applications, with an increasing demand of extending energy sources' lifetime and saving cost, it gives the possibility to combine prognostics with management strategies and use the prognostics results as the inputs to develop an effective health-conscious EMS. Fig. 1 shows a proposed system-analysis-decision loop. When the mission is initiated, the system collects the data and performs data processing and then, the pretested data goes to analysis part. Prognostics process is launched to estimate the current health state of the system and calculate the RULs. According to the prognostics results, a decision is made by implementing EMS to distribute the demanded power to multiple energy sources with the objectives to prolong the system's lifetime and/or reduce economic cost. The loop ends until the system reaches its end of life (EOL), which will be put into maintenance or replaced.

Studies on how to develop EMSs based on prognostics are rarely found, a deep thinking and standards proposal are
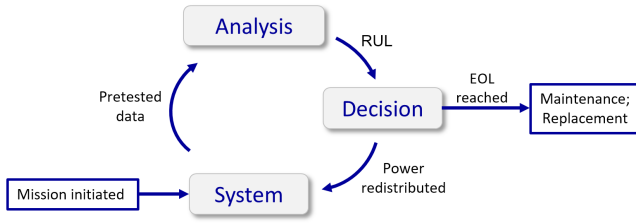
Fig. 1. The system-analysis-decision loop

demanding. This paper intends to propose a general guideline on this subject and find a solution to mitigate the degradation of the battery. The following sections are arranged as follows: system configuration is discussed in Section II which gives the hypothesis as well as the vehicle configuration. Section III introduces the prognostics process using particle filter algorithm, while implementing the EMS based on fuzzy logic control is presented in Section IV. Finally, conclusion and some perspectives are given.

II. SYSTEM CONFIGURATION

A. Studied vehicle characteristics

The simulation of this work is executed based on the vehicle introduced in [1], which is a commercial Tazzari Zero electric vehicle with a modification in its energy storage system. The control scheme and the detailed characteristics of the vehicle are presented in Fig. 2 and Tab. I.

TABLE I
BATTERY/FUEL CELL ELECTRIC VEHICLE CHARACTERISTICS

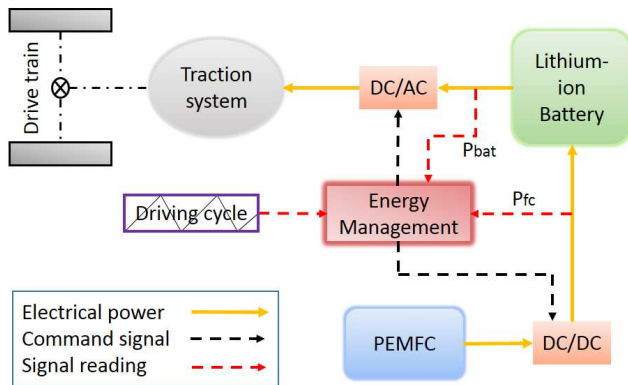| Components	Characteristics
Fuel cell	40-60V, 16kW, maximum current 400A
Inductors	5.5mΩ, 0.25mH
Battery	80V, 40Ah, LiFePO4
Electric drive	15kW induction machine
Vehicle mass	698kg

Fig. 2. Control scheme of the studied vehicle

As it is seen from Fig. 2, the battery is directly connected to the bus and used as the primary energy source, while the fuel cell is connected by a boost DC/DC converter and it is used to recharge the battery whenever it is needed. The function of the fuel cell is a range extender. The desired strategy of this work is to obtain a reference fuel cell current (Ifc_{ref}). The detailed modelling and control structure design of this vehicle can be found in [1].

B. Hypothesis

1) Operation conditions: Since the operation conditions (temperature, humidity, reaction pressure, etc.) are not always ideal and keeps changing in road driving condition, their influence on energy sources' performance is inevitable. However, under simulation conditions, it is assumed that the operation conditions are always controllable and can be regulated to their optimal values.

2) Degradation: Ageing effects are assumed to be the only considered cause for the energy source's performance degradation, while the sudden destruction on the components (open circuit, short-circuited faults, etc.) or some extreme operation conditions (extreme temperature, extreme humidity, etc.) are not taken into account. For the fuel cell, the fuel starvation is assumed to never happen. Besides, degradation phenomenon on each energy source is considered to be independent of each other. In other words, there are no added degraded effects to energy sources when they are hybridized in the system.

3) EOL definition: The system-analysis-decision loop will keep its function until the EOL of one of the energy sources is reached. According to the US Department of Energy (DoE), the EOL of the fuel cell happens when it loses 10% of its initial performance (voltage, power, etc.) [20]. For a rechargeable battery, its cycle life ended when the capacity fades beyond the acceptable limit of 20%-30% [21].

4) Horizon of the study: Most electric vehicles spend more than 90% of the time unused or in parking mode in their daily application and the ageing of battery and fuel cell takes place all the time during vehicles' parking mode and degradation mode [22]. However, with limited experiment time and condition, accelerated ageing is considered in the study.

III. PROGNOSTICS BASED ON PF ALGORITHM

EMS is responsible for distributing the power between multiple energy sources and finding the best operating point to mitigate the degradation of the energy sources, while the EMS based on prognostics relies on the information given by the prognostics process, e.g., the RULs. RUL is defined based on the EOL thresholds, which is a period that denotes how long the energy sources could remain in usage. This section gives an example on how to perform battery prognostics with particle filter algorithm. In this case, the failure threshold of the battery's capacity is set as 30% loss of its original value.

A. Prognostics with particle filter

Particle filter is a technique for implementing recursive Bayesian filter by Monte Carlo sampling and the idea is to

represent the posterior density by a set of random particles which have been allocated with associated weights and to adjust the weights of the particles based on measurements. Finally, the samples (particles) are weighted to calculate the estimates based on these samples and weights. It is described by the following process:

- *Predition*: Particles are first initiated and propogated from the state $k-1$ to the state k. The prior pdf $p(\mathbf{x}_k \mid \mathbf{z}_{1:k-1})$ is obtained based on the (1).

$$p(\mathbf{x}_k \mid \mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k \mid \mathbf{x}_{k-1})p(\mathbf{x}_{k-1} \mid \mathbf{z}_{1:k-1})d\mathbf{x}_{k-1} \tag{1}$$

- *Update*: The posterior density $p(\mathbf{x}_k \mid \mathbf{z}_{1:k})$ is calculated based on (2) once a new measurement $\mathbf{z}_k$ is available. This probability represents how much the prediction is matching with the measurement and weights are given to each particle according to this probability.

$$p(\mathbf{x}_k \mid \mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k \mid \mathbf{x}_k)p(\mathbf{x}_k \mid \mathbf{z}_{1:k-1})}{p(\mathbf{z}_k \mid \mathbf{z}_{1:k-1})} \tag{2}$$

- *Re-sampling*: Particles with lower weights are eliminated while particles with higher weights are duplicated to avoid the degeneracy of the filter.

The above steps refer to the learning phase of particle filter, which is used to track the performance of the observed variable. To implement prognostics, a prediction phase is required. It should be mentioned here that the prediction phase should be distinguished from the prediction step which is used to propagate the particles. Once the performance of the system is learned and the parameters are adjusted, the state $\mathbf{x}_k$ is propagated to $\mathbf{x}_{k+1}$ without measurements and calculating the probabilities. The entire process of implementing prognostics based on particle filter is represented in Fig. 3.
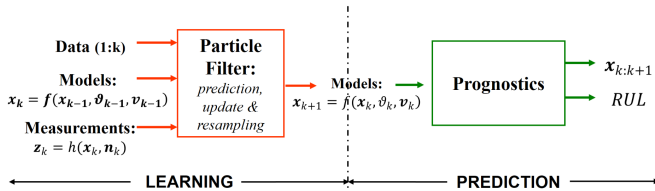

Fig. 3. Implementing prognostics with particle filter

B. Estimating RULs

The degradation information contained in the data is of great importance when predicting the RULs through prognostics. However, degradation phenomenon of the battery in electric vehicles comes from various internal and external factors, especially in road driving conditions. The rechargeable battery doesn't undergo regular charge and discharge cycles due to the various temperature, power demand and other uncertain issues on the road. Therefore, estimating the RUL of a random used battery is significant in our case. Here, prognostics is performed with a randomized battery usage dataset from the

Prognostics Center of NASA, where the battery is continuously operated using a sequence of charging and discharging currents between -4.5A and 4.5A (selecting a charging or discharging current at random from the set -4.5A, -3.75A, -3A, -2.25A, -1.5A, -0.75A, 0.75A, 1.5A, 2.25A, 3A, 3.75A, 4.5A) and capacity is checked up every 1500 steps. The current and the voltage of the first 50 steps are shown in the following Fig. 4.
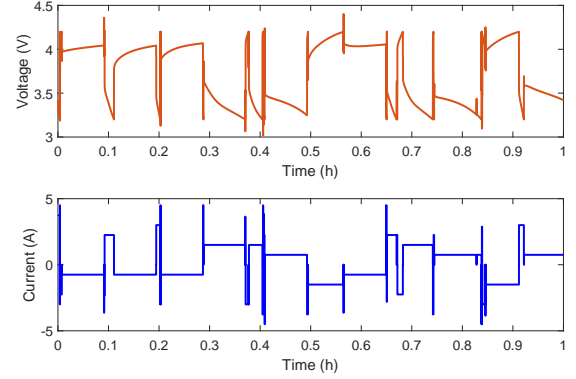

Fig. 4. Current and voltage of the first 50 steps

In our particular case, the battery's capacity loss is chosen as an indicator of degrading states. Consequently, the state model represents the maximum available capacity through time and since the capacity noisy measurements are available in the dataset, there is no need to construct an observation function. Given the data available and the problem framework, the following formulation is adopted:

$$x_{k+1} = (a \cdot e^{b(t_{k+1}-t_k)} + c \cdot e^{d(t_{k+1}-t_k)}) \cdot x_k \tag{3}$$

Predictions are made several times through the battery's entire life and each prediction is calculated 100 times in order to evaluate the dispersion of the results given by the particle filter. An example is given in Fig. 5. It represents one prediction among the 100 for a training with 540 hours applied to the studied battery using the pre-defined model (3).

In fact, after each propagation, a new distribution of the particles is obtained. All these distributions can not be represented at the same time, so the curve is plotted with the top of the particles distribution and the RUL distribution is the final particles distribution when the threshold is reached. To avoid the dispersion of the results, each prediction should be repeated at least 100 times and the recorded RUL is the median of the normal distribution of the 100 trials.

C. Acceptable error

Errors in the prediction of RULs have two possibilities: either the estimation is larger than the actual RUL, or the estimation is smaller than the actual one. The former one represents a late estimation, which is more serious because a delay of knowing the failure of the energy source tends to cause a total shut-down of the system and leave no time for
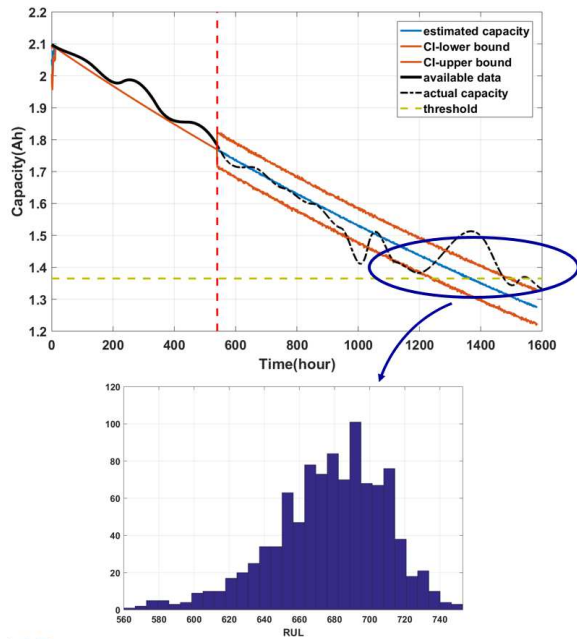
Fig. 5. Prognostics results and RUL distribution for a 540 hours long training

Fig. 6. Scheme of fuzzy logic control

Fig. 7. Membership functions for three inputs (Pdem, SOCbat, RULbat) and one output (ifc)

rescheduling. According to [2], an error of 8% is acceptable in this case. However, early prediction is less dangerous compared to the late one so that it allows higher flexibility in the estimation error. Although it may cause extra cost in maintenance, an error up to 16% is acceptable in this case. In the prediction above, the estimated EOL of the battery happens at 1365 hours and compared to the actual EOL (1476 hours), the error is 6.8%, which is in the acceptable range.

IV. IMPLEMENTATION OF EMS

A. Fuzzy logic control

Since the demanded power is divided by a high-pass filter in this vehicle model, the fuzzy logic controller used for this study is designed to meet a basic objective: Maintaining the SOC of the lithium-ion battery in a given range. The lower bound of the range allows the battery to have adequate power for the traction system. The higher bound of the range allows the battery to recover the kinetic energy during the braking phase.

Generally, fuzzy logic energy management must first ensure that the output power of the electric motor always meets the power demand of the driving cycle and the energy sources are working in their efficient regions. In this paper, SOC and RUL of the battery are added as the second and the third input variables of the fuzzy logic controller and the output variable is the required fuel cell current. The scheme of the controller is shown in Fig. 6.

After repeated tuning, the membership functions of three inputs and one output are designed as Fig. 7. Rules of the fuzzy logic controller are designed with the objectives to not only meet the power demand but also mitigate the battery
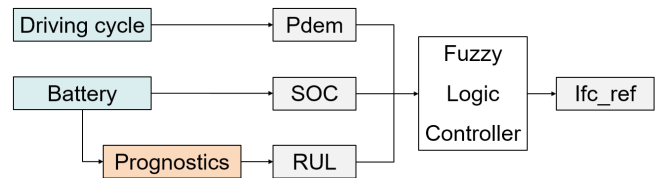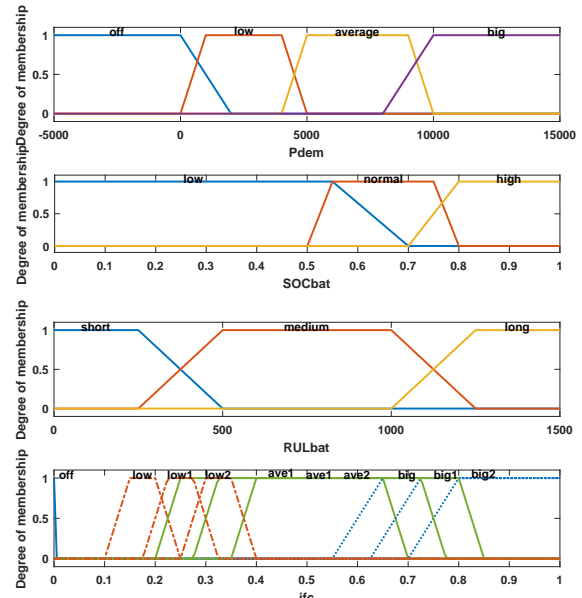
degradation. Following aspects are considered for the battery's health:

- Reducing the high charge/discharge current;
- Limiting the battery SOC in the desired range. Generally, the desired battery SOC level is within a range of 30% to 90% for vehicle applications [23].
- Limiting the depth of discharge (DOD) to be not too high. According to [24], the DOD of the battery should never be higher than 75%.

The utilized rules are represented in Tab. II. The main idea of these rules is to lower down the battery current, which means to level up the fuel cell current whenever the SOC of the battery decreases or the RUL of the battery shortens. The sort of fuzzy system is Mamdani, while the inference mechanism is AND (minimum operator) and the diffuzication mode is centroid.

B. Battery degradation calculation

It should be mentioned that in vehicle applications, the lithium-ion battery usually exists in a pack but not cells. A battery pack used in an electric vehicle is composed of a number of battery cells in series and in parallel. Cells wired

No.	Pdem	SOC	RUL	ifc
1	off	low	short	high2
2	off	low	medium	high1
3	off	low	long	high
4	off	medium	short	low2
5	off	medium	medium	low1
6	off	medium	long	low
7	off	high	short	off
8	off	high	medium	off
9	off	high	long	off
10	low	low	short	high2
11	low	low	medium	high1
12	low	low	long	high
13	low	medium	short	low2
14	low	medium	medium	low1
15	low	medium	long	low
16	low	high	short	off
17	low	high	medium	off
18	low	high	long	off
19	average	low	short	high2
20	average	low	medium	high1
21	average	low	long	high
22	average	medium	short	average2
23	average	medium	medium	average1
24	average	medium	long	average
25	average	high	short	off
26	average	high	medium	off
27	average	high	long	off
28	high	low	short	high2
29	high	low	medium	high1
30	high	low	long	high
31	high	medium	short	high2
32	high	medium	medium	high1
33	high	medium	long	high
34	high	high	short	off
35	high	high	medium	off
36	high	high	long	off

where Q_{max} is the maximum available capacity and $i_{bat-nom}$ is the nominal battery current. $Dbat$ denotes the degradation degree of battery's capacity and $Dbat \in [0, 1]$.

C. Results and discussion

The Worldwide harmonized Light vehicles Test Cycles (WLTC) Class 2 is selected as the test driving cycle, which has a total duration of 1478s. Since the time period of this cycle is not enough for demonstrating the degradation of battery, it is repeated until 1500 hours to generate the dataset for the simulation. To save the simulation time and to validate the effectiveness of the strategy, a 200 hours long period between the 150th hour to the 350th hour is considered. The prognostics process happens at the time instant of the 200th hour, which gives the estimated RUL signal to the fuzzy logic controller.

Fig. 8 shows the output power of the bus and the components, the battery and the fuel cell, for a period of 2000 seconds. It is clear that the demanded power is distributed to the battery and the fuel cell while the battery absorbs most of the peaks and the fuel cell compensate to the demanded power.
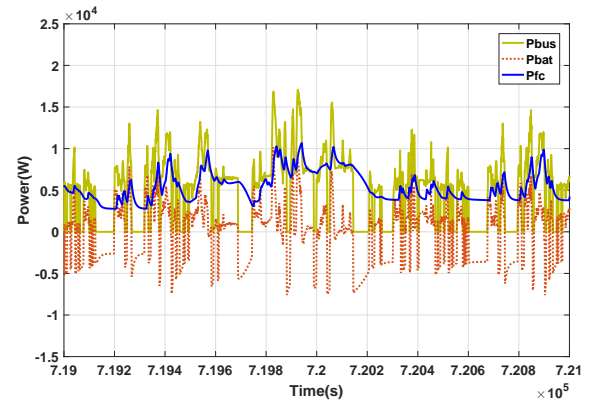

Fig. 8. Power distribution of the bus, the battery and the fuel cell

Fig. 9 plots the SOC of the battery using the designed EMS, which increases a little bit when the RUL changes. As it is shown, the SOC of the battery is always maintained in the range 0.6-0.8, which also helps to mitigate the battery degradation.

Besides, according to (5), the degradation degree of the battery is calculated and plotted in Fig. 10. According to the results, a degradation reduction of 4.75% is achieved after giving the RUL input, which verifies the effectiveness of the designed strategy. Besides, in order to exhibit more significant results, this study should be performed on a longer time period.

V. CONCLUSION

This paper proposed a real-time EMS based on prognostics, which is found to be a possible solution to take automatic corrective actions on the hybrid system and improve the durability of the battery. A global system-analysis-decision loop of implementing the EMS based on prognostics is proposed at the first and then, prognostics process is presented to show

in series aim to increase the supplied voltage while cells in parallel are used to increase the entire pack capacity. The pack capacity is calculated by the following equation [12]:

$$C_{bat} = n_{bat} m_{bat} C_{bat_{cell}} \qquad (4)$$

where n_{bat} is the number of battery cells in series and m_{bat} is the number of battery cells in parallel. Degradation in each cell is not exactly the same so that the pack capacity is taken into account when considering the degradation of the battery.

The battery degradation depends on its SOC and on the power transients. For example, high currents and especially high recharge currents in the battery reduce its lifetime. A battery degradation function can be calculated as [1]:

$$Dbat(t) = \frac{1}{Q_{max}} \int_0^t F(SOC)G(i_{bat})|i_{bat}(t)|dt \qquad (5)$$

with

$$F(SOC) = 1 + 3.25(1 - SOC)^2 \qquad (6)$$

$$G(i_{bat}) = \begin{cases} 1 + 0.45\dfrac{i_{bat}}{i_{bat-nom}} & ,\text{if } i_{bat} \geq 0 \\ 1 + 0.55\dfrac{|i_{bat}|}{i_{bat-nom}} & ,\text{if } i_{bat} \leq 0 \end{cases} \qquad (7)$$
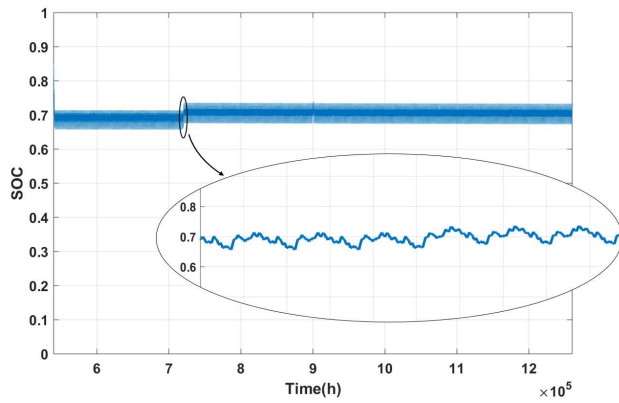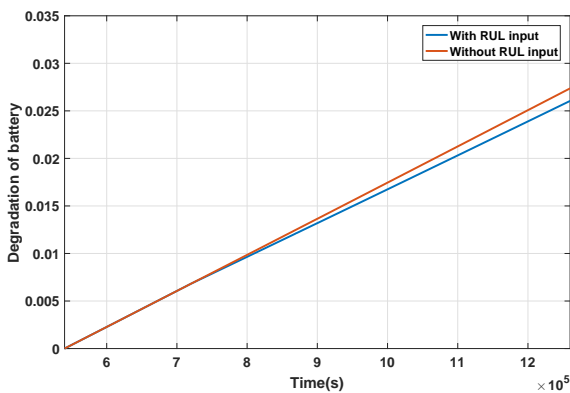
Fig. 9. SOC of the battery

Fig. 10. Degradation of the battery

how RUL is estimated. Finally, an EMS based on fuzzy logic is proposed and simulation results are discussed. This field of study has just under proposition and further efforts will be made by the authors in the near future to improve the optimality of the strategy.

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