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Enhancement of Stress Cycle-counting Algorithms for Li-ion Batteries by means of Fuzzy Logic

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***Abstract*— The rainflow algorithm is one of the most commonly used tools for studying stress conditions of a wide variety of systems, including power electronics devices and electrochemical batteries. One of the main drawbacks of the algorithm is the trade-off between data compression and the loss of information when classifying the stress cycles into a finite amount of histogram bins. This paper proposes a novel approach for classifying the stress cycles by using fuzzy logic in order to reduce the quantization error of the traditional histogram-based analysis. The method is tested by comparing the accumulated damage estimations of two support-vector regression algorithms when trained with each type of cycle-counting procedure. NASA's randomized battery usage data set is used as source of stress data. A 50% error reduction was observed when using the fuzzy logic-based approach compared to the traditional one. Thus, the proposed method can effectively improve the accuracy of diagnosis algorithms without penalizing their performance and memory-saving features.**

***Index Terms*— degradation, diagnosis, energy storage, fuzzy logic, Li-ion battery, load collective, rainflow, state of health, stress cycles**

I. Introduction

WITH the increasing concerns about human-induced climate change, the world is swiftly pushing for deep changes in many different areas. Two of the most important ones are power systems and transportation, where the goal is to substitute highly-polluting fossil fuels with electricity generated by renewable energy sources (RESs). In both cases, energy storage systems (ESSs) play a key role: in the former, they are used to guarantee a steady power supply since RESs cannot work on-demand, while in the latter they must be able to cover drivers' daily needs comfortably, avoiding range anxiety. Despite its recent accelerated development, battery technology is still expensive and can represent a hefty part of the application's cost. Therefore, understanding battery degradation and trying to extend their lifetime is a very interesting tool for reducing ownership costs, thus making these projects more attractive and stimulating their adoption.

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A. State of the Art

The rainflow counting algorithm has been employed as a method for fatigue analysis of materials for several decades, and various implementations have been proposed throughout the years [1], [2]. Favoured by the great research interest on RESs and electric vehicles (EVs), this technique has recently been applied to power electronics devices [3], [4] and batteries [5]–[7].

Reference [5] was the first attempt to apply this technique to EVs, where both the state of health (SoH) and the remaining useful life (RUL) were estimated by means of a support-vector regression (SVR) algorithm. The input vector was composed of the capacity at the beginning of the cycle, as well as the corresponding load collective based on state of charge (SoC) and temperature cycles. The same team used this approach for batteries from a hybrid EV in [6]. In this case, the load collectives contained information regarding SoC, mean temperature, mean voltage and C-rate. In [7], a similar idea was applied to a stationary ESS, but rainflow counting was only applied to average SoC and depth of discharge (DoD). Then, degradation was estimated via a damage model with a polynominal function. Lastly, histogram-based classification of stress variables was also studied in [8]. Rather than using the rainflow algorithm to obtain cycle counts, the accumulated energy throughput of each of the stress levels was measured. The stress variables considered were SoC and temperature. The statistical properties of these histograms were fed to various machine-learning algorithms to predict the battery's RUL, having artificial neural networks the lowest error.

Although good overall accuracy was obtained in the aforementioned works, all of them employed traditional (i.e., crisp) histograms. This step introduces a quantization error since the information stored in the histograms does not exactly represent the original stress signal. The magnitude and impact of this error is difficult to quantify and it is usually disregarded. In this paper, the quantization error problem is addressed by implementing a fuzzy logic-based classification algorithm.

II. Fuzzy Stress-Cycle Classification

One of the main applications of the rainflow method is to record and evaluate the accumulated damage experienced by a system after being subjected to some stress factor, and to predict its remaining useful life under a certain mission profile. Given such a stress signal, the algorithm outputs a collection of cycles with the corresponding amplitude of the stress variable, which, generally, is unconstrained and can take any value. In order to perform system diagnosis and prognosis (e.g., using Miner's rule), the amplitudes of the stress cycles are usually discretized by means of histograms (also referred to as load collectives), that is, counting the amount of cycles that have an amplitude within a certain interval.

A. The quantization error problem

As aforementioned, a generic diagnosis and prognosis algorithm based on rainflow counting can be summarized in four steps:

1) Acquisition and pre-processing of the stress variable's time series.
2) Detection and identification of half- and full-cycles by the rainflow algorithm.
3) Classification of cycles into histogram bins depending on their amplitude, forming load collectives (LCs).
4) Application of a stress analysis algorithm, such as Miner's rule or other specific damage models.

One of the main advantages of this methodology is that it allows for condensing a large amount of information into a compact histogram. This simplification, however, comes at the cost of losing resolution in the stress variable, since the amount of bins used is finite. Therefore, there is a trade off between data compression and resolution. In any case, this leads to worse performance of the diagnosis and prognosis algorithms.

A simple example of the quantization error problem is illustrated in Fig. 1, where the horizontal axis corresponds to the stress variable and the vertical one to the amount of cycles at each stress level. The first, second and third bins are defined by $x \in (0, 1]$, $x \in (1, 2]$ and $x \in (2, 3]$, respectively. These are delimited by the purple, blue and red dotted lines, respectively. In the traditional approach (i.e., crisp histograms), points $\alpha = 1.2$ and $\beta = 1.8$ would be assigned to the second bin, while point $\gamma = 2.2$ would belong to the third one. However, given the distances from point β to α and γ, it would be fair to assume that the information it carries is closer to the latter. This is due to the fact that, in general, stress variables are continuous, analog signals where similar values will produce similar effects. An obvious solution to this problem would be to increase the resolution by adding more bins to the histogram, but this would have a negative effect on the computational requirements of the algorithm. This paper proposes using fuzzy logic to mitigate this problem.

B. Fuzzy load collectives

Fuzzy logic (FL) is an artificial intelligence technique that has been largely applied for modelling and control tasks of a wide variety of systems [9]. One of the main advantages of FL is that it allows to map an analog variable into a discrete domain which, unlike regular histograms, does not have rigid, exclusive boundaries. This implies, for example, that values in the vicinity of the border between two bins would be simultaneously assigned to both of them with some membership grade (μ). This is referred to as *fuzzyfication* and it is exemplified in Fig. 2 for the same points as in the previous case, but with two linear-saturation membership functions (A and B) instead of fixed-width histogram bins. In this case, point γ is clearly under B and away from A, but points α and β belong to both A and B. For the membership functions shown, the membership grades can be computed following (1) and (2), respectively.

$$\mu_A(x) = \begin{cases} 1\,, & \text{if } x \leq x_{i,A} \\ \frac{x_{f,A} - x}{x_{f,A} - x_{i,A}}\,, & \text{if } x_{i,A} < x < x_{f,A} \\ 0\,, & \text{if } x \geq x_{f,A} \end{cases} \qquad (1)$$

$$\mu_B(x) = \begin{cases} 0\,, & \text{if } x \leq x_{i,B} \\ \frac{x - x_{i,B}}{x_{f,B} - x_{i,B}}\,, & \text{if } x_{i,B} < x < x_{f,B} \\ 1\,, & \text{if } x \geq x_{f,B} \end{cases} \qquad (2)$$

where $x_{i,A} = x_{i,B} = 1$, $x_{f,A} = x_{f,B} = 2$. Thus, the membership grades of the points are $\mu_A(\alpha) = 0.8$, $\mu_B(\alpha) = 0.2$, $\mu_A(\beta) = 0.2$, $\mu_B(\beta) = 0.8$, $\mu_A(\gamma) = 0$ and $\mu_B(\gamma) = 1$. Compared to the original example, the novel algorithm classifies points α and β in both sets A and B with an associated degree of membership. This process is repeated for each cycle while aggregating the obtained results. For the present example, the resulting load collective would be $N_A(\mathbf{x}) = \sum_i \mu_A(x_i) = 1$ and $N_B(\mathbf{x}) = \sum_i \mu_B(x_i) = 2$.

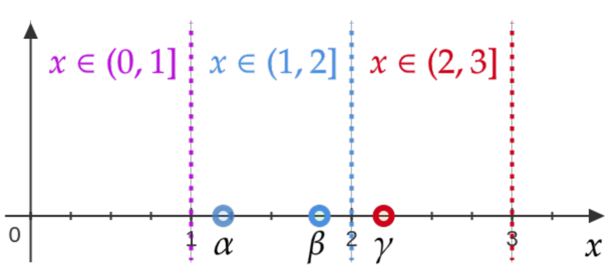

Fig. 1. Quantization error problem

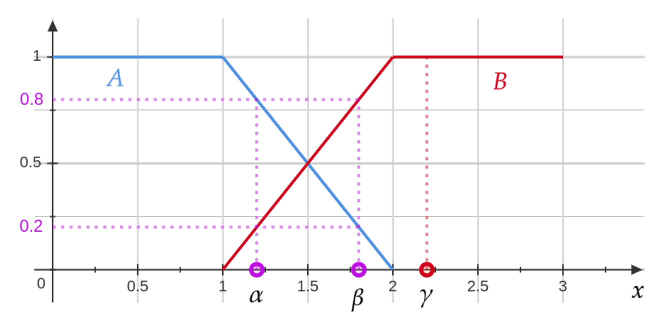

Fig. 2. Fuzzyfication of one variable with two linear-saturation membership functions

In an analogy to the traditional method, the membership grade would be a binary function which would yield $\mu = 1$ if the cycle's amplitude fell within a bin's interval and $\mu = 0$ otherwise.

III. Accumulated damage estimation

Although the approach proposed in this paper could be applied for stress-cycle analysis in any application, it was chosen to focus on electrochemical batteries given the great research and industrial interest in developing accurate diagnosis and prognosis algorithms.

In both EV and stationary ESS applications, the main metric used to assess a battery's degradation (or damage) level is the state of health, which quantifies the energy storage capacity at a given instant compared to a reference value. It is computed as in (3).

$$SoH = \frac{Q_{max}}{Q_{ref}} \cdot 100\% \tag{3}$$

where Q_{max} is the maximum available capacity of the battery at a given instant and Q_{ref} is the reference capacity, usually taken as the rated capacity as given by the manufacturer. It is usually considered that a battery has reached its end of life whenever $\text{SoH} = 80\%$.

Since the purpose of this paper is not to derive new damage models, but to compare the traditional and the novel cycle-counting algorithms, a simple support-vector regression (SVR) algorithm [10] is implemented to estimate the degradation associated to a particular mission profile. More specifically, it takes as inputs the aggregated load collectives and outputs the accumulated damage associated to that operation history. For simplicity purposes, only two stress factors are considered as predictors, namely the depth of discharge and the average current over one cycle. This is in agreement with the existing literature, which establishes large DoD and C-rate values as major degradation causes [11].

The inputs to the SVR are obtained by applying the rainflow and cycle-classification algorithms from the beginning of the time series up to a given instant, while the ground truth for the outputs is obtained from the reference performance tests. This process is illustrated by the flowchart in Fig. 3.

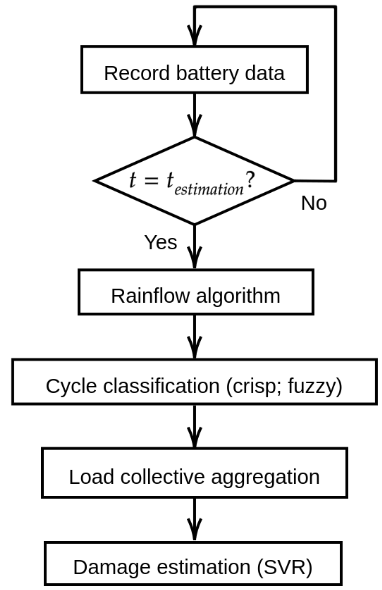

Fig. 3. Rainflow-based damage estimation algorithm

IV. Experimental Validation

In order to draw a comparison between both approaches, an SVR model is created for each case, that is, crisp and fuzzy. The initialization parameters are the same for both of them, and they are trained and tested with the samples corresponding to the same cycles obtained from the rainflow algorithm.

A. Battery data set

NASA's randomized battery usage data set [12], [13] contains data from a total of 28 Li-ion cells cycled continuously at constant ambient temperature following mission profiles generated by random-walk processes. Periodic reference performance tests were conducted to measure the cells' maximum available capacity. Although the employed mission profiles are not based on real-world scenarios, the great diversity of excitation C-rates makes this data set a good fit for evaluating the methodology proposed in this paper.

After thoroughly processing and analyzing the entire data set, cell *RW5* was selected to validate the proposed approach. The cell and cycling details are summarized in Table I.

TABLE I
RW5 CELL INFORMATION

Form factor	18650, Cylindrical
Rated capacity	2 Ah
Upper cut-off voltage	4.2 V
Lower cut-off voltage	3.2 V
Discharge current range	0.25 C – 2 C
Charge current	1 C

B. Cycle-classification set up

For both the crisp and fuzzy load collectives, it was chosen to use 5 bins for each variable, which means that the load collectives are 5x5 matrices. After analyzing NASA's data set and observing the SoC and C-rate levels experienced by the cells, the DoD was considered to range from 0% to 100%, while the average C-rate was considered to range between 0 A and 4.5 A. For the crisp load collectives, the bin delimiters are straightforward to obtain and are presented in Table II.

TABLE II
CRISP LOAD COLLECTIVES

Variable	Histogram bins
$\mathbf{DoD}$	$[0, 20)$; $[20, 40)$; $[40, 60)$; $[60, 80)$; $[80, 100]$
$\mathbf{I_{mean}}$	$[0, 0.9)$; $[0.9, 1.8)$; $[1.8, 2.7)$; $[2.7, 3.6)$; $[3.6, 4.5]$

For the fuzzy load collectives, however, there are many degrees of freedom (membership functions types and parameters) and the combinations are potentially infinite. For this proof of concept, identical triangular membership functions are employed due to their simplicity. They are characterized by only 3 parameters: the starting point (x_i), the peak (x_p) and the ending point (x_f). Thus, the degree of membership is computed using (4).

$$\mu_\Delta(x) = \begin{cases} 0\,, & \text{if } x \leq x_i \\ \frac{x-x_i}{x_p-x_i}\,, & \text{if } x_i < x < x_p \\ \frac{x_f-x}{x_f-x_p}\,, & \text{if } x_p < x < x_f \\ 0\,, & \text{if } x \geq x_f \end{cases} \tag{4}$$

For the upper and lower ends of the fuzzy histograms, linear-saturation membership functions are employed (see Fig. 2). The membership functions and their parameters for both stress factors are presented in Table III, and shown in Figs. 4 and 5. The values in curly brackets correspond to x_i, x_p and x_f.

TABLE III
FUZZY LOAD COLLECTIVES MEMBERSHIP FUNCTIONS

MF	Type	Parameters
$\mathbf{DoD_1}$	Left linear saturation	$\{0, 25\}$
$\mathbf{DoD_2}$	Triangular	$\{0, 25, 50\}$
$\mathbf{DoD_3}$	Triangular	$\{25, 50, 75\}$
$\mathbf{DoD_4}$	Triangular	$\{50, 75, 100\}$
$\mathbf{DoD_5}$	Right linear saturation	$\{75, 100\}$
$\mathbf{I_{mean,1}}$	Left linear saturation	$\{0, 1.125\}$
$\mathbf{I_{mean,2}}$	Triangular	$\{0, 1.125, 2.25\}$
$\mathbf{I_{mean,3}}$	Triangular	$\{1.125, 2.25, 3.375\}$
$\mathbf{I_{mean,4}}$	Triangular	$\{2.25, 3.375, 4.5\}$
$\mathbf{I_{mean,5}}$	Right linear saturation	$\{3.375, 4.5\}$

The results of applying the rainflow and cycle-classification algorithms to the entire time series are shown in Figs. 6 and 7 for the crisp and fuzzy approaches, respectively. Note that, in Fig. 6, the x- and y-axis ticks mark the borders between bins, whereas in Fig. 7 the labels DoD_i, $I_{mean,i}$ are aligned with the peak point (x_p) of the corresponding membership function.

It is clear that, in the proposed approach, the cycles are assigned in a more homogeneous way than in the traditional one. This is due to the fact that most cycles are now classified into four bins at the same time (two per stress variable), but with a lower contribution (i.e., their membership grade). This also results in the fuzzy load collectives having higher values than in the discrete case, although the plots have been normalized to make comparisons easier.

C. Results

In order to validate this novel approach, the SVR models are trained to predict the accumulated capacity loss of the battery at a certain instant based on the aggregated load collectives up to that moment. The root-mean-squared error (RMSE) and mean absolute error (MAE) when making predictions on the test data set are used as metrics to compare the performance

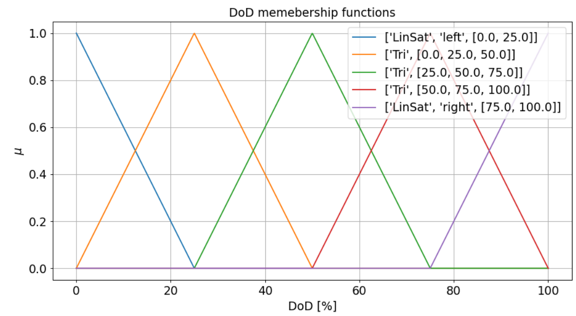

Fig. 4. Membership functions for fuzzy classification of DoD cycles

of the traditional and novel approaches. These are computed as in (5) and (6), respectively.

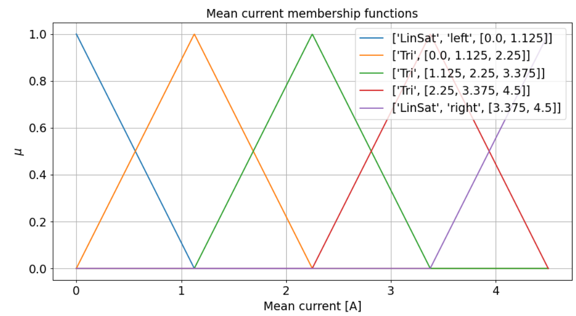

Fig. 5. Membership functions for fuzzy classification of mean current cycles

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2} \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - y_i\right| \tag{6}$$

where $\hat{y}_i$ and y_i are the estimated and measured accumulated damage values of the i^{th} sample, respectively, and N is the number of samples.

TABLE IV
DEGRADATION ESTIMATION RESULTS

Data set	Method	RMSE	MAE
Train	Crisp	0.029	0.021
	Fuzzy	0.019	0.01
Test	Crisp	0.027	0.018
	Fuzzy	0.016	0.011

It is observed that the proposed approach performs significantly better than the classic one, with an error reduction of around 50% in both training and testing. This is thanks to the cycles being classified in a more realistic way, which reduces the aforementioned quantization error.

Lastly, it is worth discussing the data size reduction obtained by applying the rainflow algorithm. The original data set

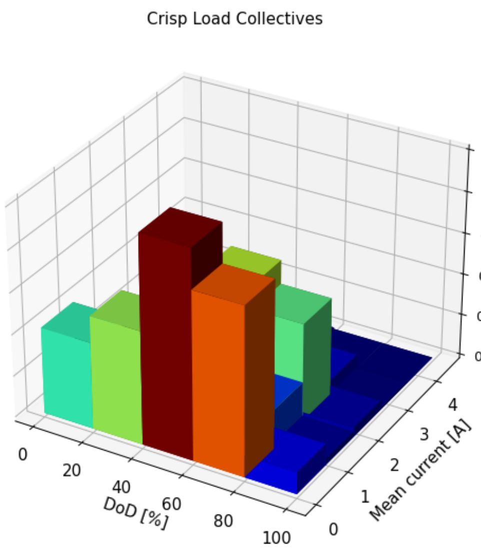

Fig. 6. Crisp load collectives

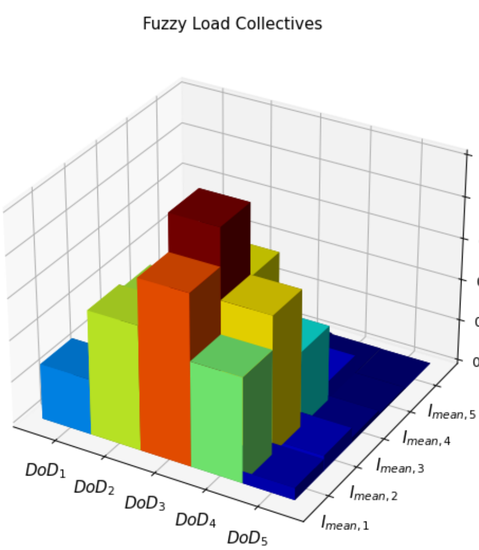

Fig. 7. Fuzzy load collectives

contains 2857788 samples, each of them including 3 variables (time, SoC, current). On the other hand, the load collectives have a total of 25 elements. Assuming the data type is 32-bit float in all cases, this results in a total size of 34.3 MB for the original time series, while the load collectives take only 100 B. This confirms the significant memory savings of the rainflow algorithm, at the cost of losing some information.

V. Conclusion

Accurate battery damage models are essential to make reliable remaining useful life predictions. To that end, a novel enhancement of the rainflow cycle-counting algorithm has been introduced, which uses fuzzy logic in order to reduce the quantization error present in the standard algorithm.

Results have shown that the FL-based algorithm performs much better than its traditional counterpart. On the other hand, its requires a bigger effort to set up the membership functions' types and parameters.

Future developments of the approach proposed in this paper include a wider variety of membership functions, parameter optimization, a more comprehensive degradation analysis, as well as more advanced machine learning-based damage models.

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