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Comparative study of anomaly detection techniques for monitoring Lithium Iron Phosphate – LiFePO4 batteries.

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Abstract

This research analyzes and compares the application of different intelligent supervised classification techniques for detecting anomalies in power cells. For this purpose, a labeled dataset is obtained and generated in which samples of the different charge and discharge cycles of a Lithium Iron Phosphate - LiFePO4 (LFP) battery commonly used in electric vehicles are collected. The final classifiers present successful results.

1 Introduction

The current state of climatic emergency caused by global warming as a consequence of greenhouse gas emissions has led many countries and organizations to establish policies to reduce these gases. For example, in 2021, the European Union (EU) signed the European Climate Law, which is part of the European Green Pact, to achieve a reduction of at least 55% in greenhouse gas emissions (compared to 1990 emissions), with the final goal of reaching climate neutrality (0 emissions) in 2050. In this context, one of the promoted actions is reducing carbon dioxide emissions in road transport since it accounts for 60.6% of total CO2 emissions in the EU [1]. For all these reasons, the EU is promoting the use of electric vehicles. In recent years, the use of electric vehicles has grown exponentially. However, this type of vehicle requires improved performance in autonomy, so the improvement of batteries is a crucial factor in promoting this type of mobility.

On the other hand, the use of batteries is not only important in electric mobility but also plays a significant role in many fields such as renewable energy generation, computing, or even portable electronics such as mobiles, laptops, etc.

Considering the above, improving the characteristics and technology of electric batteries is of great interest. Currently, most batteries are Lithium Iron Phosphate - LiFePO4 (LFP) due to its great power density, long service life, and high voltage [2]. Therefore, this paper presents a method based on intelligent supervised techniques for detecting anomalies in the charging, discharging and resting stages of Lithium (LiFePO4) batteries.

2 Materials and methods

2.1 Dataset description

To obtain the dataset, a LiFeBATT X-1P battery, composed of a LiFePO4 cell, whose nominal capacity is 8A-h, with 3.3V of nominal voltage [3], was tested for 9 cycles. Each of these cycles consisted of four phases: the charging phase, the resting phase with the battery charged, discharging phase, and the resting phase with the battery discharged. Data acquisition was performed with a sample rate of 1 Hz. Likewise, the variables that were registered were the current, voltage, the temperature of the battery measured in two different battery locations, and the SOC, which refers to the battery charge measured in percentage. During the 9 cycles, a total of 6610 samples were registered from the charging phase, 967 samples from the resting phase with the battery charged, 6620 samples from the discharging phase, and 975 samples from the resting phase with the battery discharged, for a total of 15172 samples.

However, all the recorded data corresponds to correct battery operation, so we proceeded to generate anomalies on 25% of the recorded samples. To simulate these anomalies, and as indicated by the battery manufacturer, the temperature data was modified since this value indicates degradation. The temperature value was modified by a random percentage between 3 and 10% of its original value. It is important to note that despite using two sensors, these cells are characterized by maintaining a homogeneous temperature, so the measurements of both sensors are very similar. Due to this and to simulate a realistic behavior, the deviation is applied to the two temperature measurements.

2.2 Implemented techniques

As mentioned in the introduction, this research applies intelligent supervised classification techniques for anomaly detection. The different techniques implemented are described below.

- **Decision Trees.** The decision tree (DT) algorithm generates a tree-like classifier and is implemented by splitting the data set repeatedly using a criterion that maximizes the separation of the samples. At each splitting, the entropy decrement must be maximized.
- **Random Forest.** The Random Forest (RF) technique uses several decision trees previously trained with different data subsets. With all the decision trees trained, the random forest classification output corresponds to the class obtained in most of the decision trees.
- **K-Nearest-Neighbours.** Also known as k-NN, this classification algorithm uses the data density to label a new instance. It assesses the k Nearest Neighbours and counts the number of samples in each class to estimate the class label.
- **Artificial Neural Networks.** Artificial Neural Networks (ANN) is a technique based on using neurons placed in different layers. The neurons are connected to the neurons of the adjacent layer. Each of the weights connecting the neurons and the activation function parameters are tuned in the training process following an error minimalization criteria.
- **Support Vector Machines.** Also known as SVMs, they are based on finding a hyperplane that maximizes the minimum distance between it and the samples of each class closest to the related hyperplane.

3 Experiments and Results

Once the techniques used were analyzed, different experiments were carried out in order to find the best classifier. Firstly, the dataset was preprocessed and normalized using the z-score method (with a mean of 0 and a standard deviation of 1). Next, the different models created were trained using cross-validation with k=10. To obtain the best classifier, each method was previously tested for different values of its hyperparameters. Since the data set was unbalanced, the AUC (Area Under the Receiving Operating Curve) metric was used to compare and determine the best model since this measure is insensitive to unbalance data. In addition, Kruskal-Wallis variance analysis and Tukey comparison method are used to compare the models. Table 1 shows the results obtained with each model with their pre-tuned hyperparameters. The table shows the AUC value and the training time to represent the computational cost.

Model	AUC	Training time (s)
DT	0,986	0,518
RF	0,995	2,864
k-NN	1	0,678
ANN	0,998	68,514
SVM	0,587	304,862

Table 1: Results obtained

4 Conclusions

This paper deals with anomaly detection in LFP power cells using supervised classification techniques. The results show a high performance in all the tested techniques except in SVMs, detecting all the anomalies generated with Artificial Neural Networks. Therefore, implementing this approach could greatly interest the development and improvement of batteries.

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