Lithium iron phosphate power cell fault detection system based on hybrid intelligent system

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Abstract

Nowadays, batteries play an important role in a lot of different applications like energy storage, electro-mobility, consumer electronic and so on. All the battery types have a common factor that is their complexity, independently of its nature. Usually, the batteries have an electrochemical nature. Several different test are accomplished to check the batteries performance, and commonly, it is predictable how they work depending of their technology. The present research describes the hybrid intelligent system created to accomplish fault detection over a Lithium Iron Phosphate—LiFePO4 power cell type, commonly used in electro-mobility applications. The approach is based on the cell temperatures behaviour for voltage and current specific values. Taken into account the operating range of a real system based on a LiFePO4 cell, a large set of points of operation have been used to achieve the dataset. The different behaviour zones have been obtained by clustering as a first step. Then, different regression techniques have been used over each cluster. Polynomial regression, artificial neural networks and support vector regression were the combined techniques to develop the hybrid intelligent model proposed. The intelligent system gives very good results over the operating range, detecting all the faults tested during the validation.

Keywords: Power cell, fault detection, battery, clustering, artificial neural networks, polynomial regression, LS-SVR.

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1 Introduction

Almost all devices in the world are electric powered. From small appliances, mobiles, laptops, home applets to big industrial machinery. Electricity is present almost everywhere and even renewable generation is becoming a commodity. Electric energy storage is one of the trending solutions due to several reasons [19]. Examples of these motives are: the variation of the energy production at renewable energy installations like wind farms, the necessity of finding a substitute for fossil fuels or to supply energy to portable devices [34].

Last significant machines that resist this important movement towards being electric powered are transportation related ones. However, its inserting is unavoidable as for instance in the case of electric powertrains that are more efficient than internal combustion engines [41].

Apart from other reasons (political, social, infrastructure, etc.) the main technological problem is directly related to energy storage on-board [16]. Humankind has not solved yet how to storage electricity in an efficient way. Electrochemical solutions are very expensive compared to current solutions and also heavier, the latter also being very important for movable machines.

Then, one of the best candidates to accomplish the above mentioned problem in electric vehicles are the batteries. Nowadays, there are some studies that use computational intelligence (CI) methods and identification systems due to their embedded capability to automate and optimize tasks in process modelling directly from sensor data, monitoring, cognitive fault detection and diagnosis of batteries [12, 22, 28]. In [11, 14, 15] intelligent systems were developed to detect faults over a heat pump installation. Zhang and Canova [45] accomplish fault detection and isolation of automotive air conditioning systems using first principle models. Fault detection and isolation of bearings in a drive reducer of a hot steel rolling mill is described in [21].

Then, obtain an accurate model of the battery by means of CI systems, such as regression models, is very important to get a good fault detection system.

The classic regression models are based on multiple regression analysis (MRA) methods [31]. MRA-based methods are useful due to their applications in different subjects [24, 26, 30]; the first cite shows a model for cost prediction in the early state of projects and the second one proposes a method to evaluate suppliers performance. The main problem of these methods is their limitations in certain cases. For instances in [10, 13, 18, 31] the common trouble is its non linearity and the different ways followed to solve them with approaches based on MRA techniques. Regression techniques based on soft computing could avoid some of the problems mentioned above. Several works have been developed with this goal. In [33] the prediction state of a model predictive control system is carried out by meta-classifiers. By combining multi regression analysis and artificial neural networks (ANNs) an optimizing overbreak prediction is made in [25]. In [4] failure detection and prediction in wind turbines is achieved by using intelligent techniques.

Despite the new methods to solve regression problems, there are cases where it is not possible to achieve a good performance of the model, for instances due to the high non-linearity of the system. Clustering could be a complementary solution as a previous step to apply regression to the dataset [32]. K-means clustering algorithms are often employed with this purpose [17, 23]. With this method, the dataset is divided into subsets (clusters), depending on the features of the input data. Then, regression is made over each cluster with common characteristics. Previous works like [6–8, 20, 36, 39, 46] used similar techniques to solve other physical systems.

This study implements a hybrid intelligent model to make fault detection over the Lithium Iron Phosphate—LiFePO4 (LFP) power cell type.

To develop the model, K-means clustering algorithm was used for making groups of data with the same behaviour. Then, three different regression techniques were tested for each group, to choose the best one based on the lowest mean squared error (MSE) achieved.

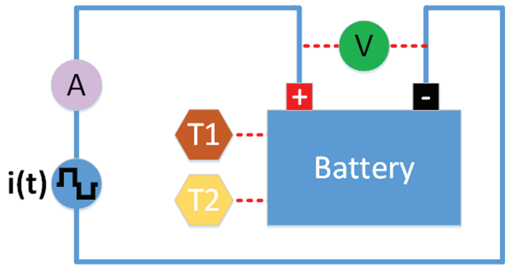

FIGURE 1. Scheme of the capacity confirmation test.

The rest of the paper is organized as follow. After this introduction, the case of study section describes the standard employed test and how the dataset was obtained to create the model for making fault detection. Then, the model approach and the tested algorithms used in the study are presented. Following, the results obtained by the novel hybrid model against the other classical models are presented. Finally, it is introduced the conclusions and future.

2 Case of study

The model has been obtained to make fault detection of a LFP power cell type. To collect the dataset, the standard capacity confirmation test was accomplished, by measuring different variables and obtaining its state of charge, defined as the ratio of its current capacity ($Q(t)$) to the nominal capacity (Q_n); ($SOC(t) = \frac{Q(t)}{Q_n}$) [1]. Measurement of SOC if done applying the direct method of voltage [42].

The scheme of the practical implementation to carry out the test is shown on Figure 1.

The developed test measures the device capacity in ampere-hour at a constant current [1]. The first step is to charge the cell to its maximum SOC. After that, the battery is discharged at constant current up to the discharge voltage limit specified by the manufacturer [1]. Once the cell is recharged to its maximum capacity, the battery capacity and the SOC are calculated at each moment.

The test was done with a battery tester that can charge and discharge the cells at constant current, and it is able to measure different parameters. These parameters are the voltage provided by the battery, the current flowing to and from the battery, its temperature and the test time.

The test scheme is shown on Figure 1. On it, it is possible to see different components like a voltmetre *(V)*, an ampere-metre *(A)* and two temperature sensors *(T1 & T2)* to measure the temperature value at two different places. Also, there is a current source that provides and absorbs the flowing current *(i(t))*.

The cell used during this test was the LiFeBATT X-1P [2]. This power cell is an LFP type, whose nominal capacity is 8000 mAh and its nominal voltage 3.3 V (manufacturer information set the maximum voltage in 3.65 V and the minimum in 2 V, in order to keep the charging current constant). During the test (shown in Figure 2), the next steps are carried out:

- (1) Charge: where the voltage increases from 3 V to 3.65 V.
- (2) Rest after a charging process: where the voltage decreases up to the nominal value of 3.3 V.
- (3) Discharge: where the voltage decrease from 3.3 V to 2 V.
- (4) Rest after discharging process: where the voltage grows up to the value of 3 V, and then the cycle starts again.

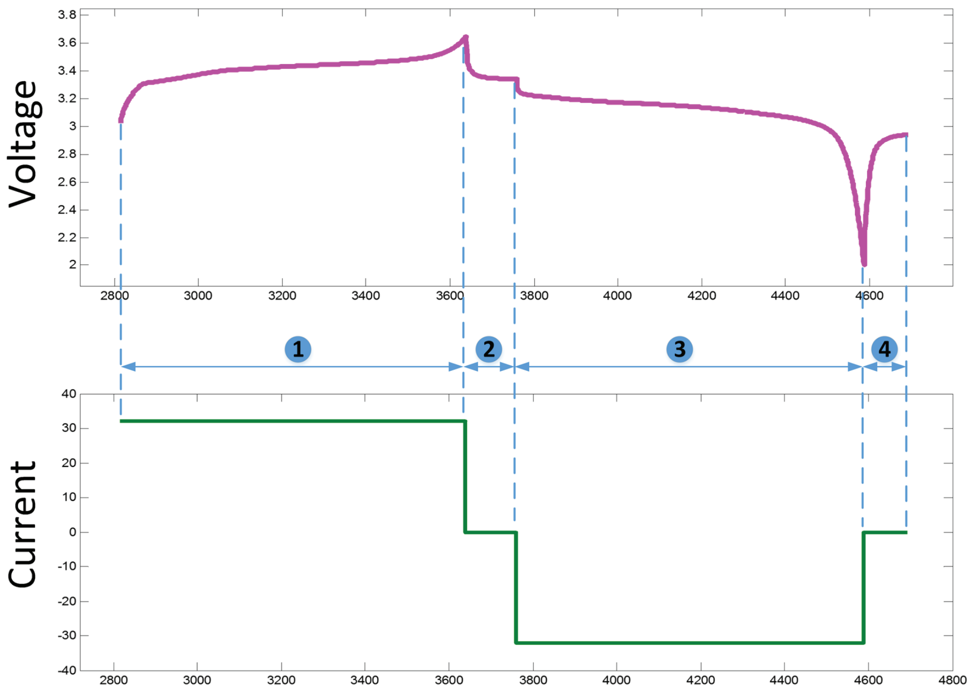

FIGURE 2. Voltage and current during one cycle test.

The analysis of voltage progress for one entire cycle is shown at the top of Figure 2. The analysis of the current (bottom of Figure 2) shows that the process carried out was done at a constant value of current. The current is positive when it flows from the source to the battery, and it is negative when it flows from the battery to the source.

With the value of current at each time it is possible to obtain the energy provided or absorbed in ampere-hour. If this energy is represented (top of Figure 3) it is possible to see how the battery SOC increases during the charging period until 100% of charge. On the other hand, the SOC of the cell decreases till its minimum value of 0% during the discharging process.

The measurement of temperatures are done with two sensors located at different places of the battery. These parameters vary cyclically depending on the state of the battery (charge, discharge, rest after charge and rest after discharge) and on its voltage. At the bottom of Figure 3, it is possible to see the temperature behaviour for each operating region. Remark that the temperature at this type of battery is a very good indicator of its health state [1].

The dataset has been obtained by carrying out the mentioned test over the power cell. The current and the voltage were registered to study the state of the battery. Two different temperatures were measured to detect malfunction on the device, if the temperature is far from the predicted one.

3 Model approach

The scheme of the model approach is shown in Figure 4. Taking into account the power cell performance and the test made, it is possible to divide the dataset in N operation ranges. Consequently, N clusters are created and, the regression models (one per output) are implemented

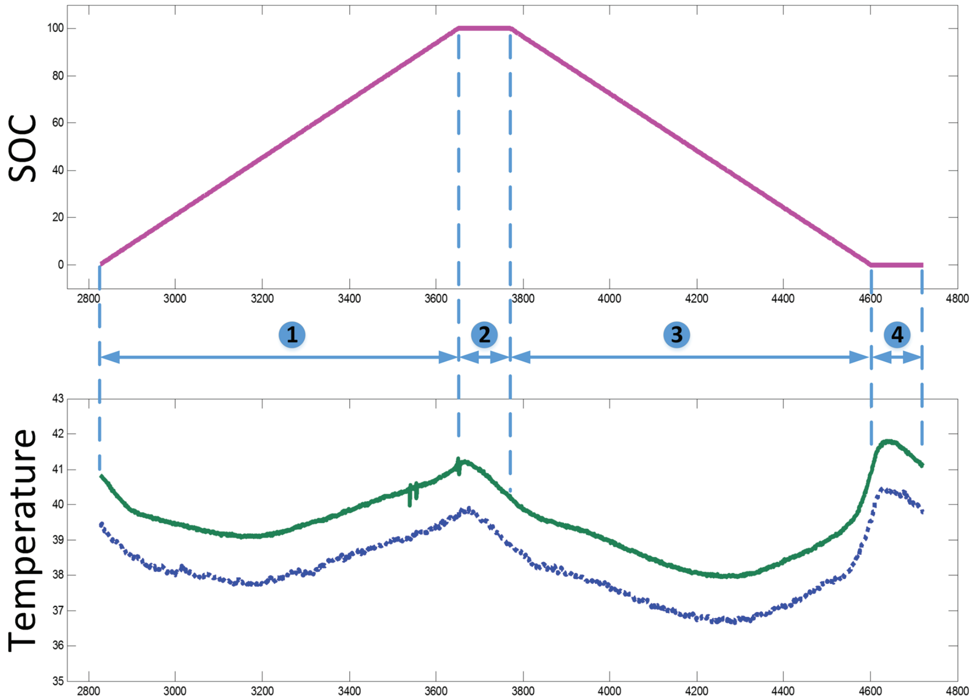

FIGURE 3. Energy balance and temperatures during one cycle test.

for each one. As shown in the Figure 4, the global model has two inputs (the real current and the real voltage) and two outputs (T1 predicted and T2 predicted). The aim of the block selector is to connect the regression models of the chosen cluster (it depends of the real current and voltage values) with the global model outputs. Then, the predicted temperatures are two inputs for the the fault verification block. This block allows of detecting a fault comparing the predicted temperatures provided by the model, with the real ones values measured at the power cell. The fault existence depends of the deviation range, which is other fault verification block input provided by the user.

3.1 Techniques used

The techniques tested in the study to achieve the best model are described below.

3.1.1 Data Clustering. The K-means algorithm. Clustering is an unsupervised technique of data grouping where similarity is measured [35, 43]. Clustering algorithms try to organize unlabelled feature vectors into clusters or groups, in such a way that samples within a cluster are similar to each other [27]. K-means algorithm is a commonly used partitional clustering algorithm with square-error criterion, which minimizes error function shows in equation (1).

$$e = \sum_{k=1}^{C} \sum_{x \epsilon Q_k} \|x - c_k\|^2 . \tag{1}$$

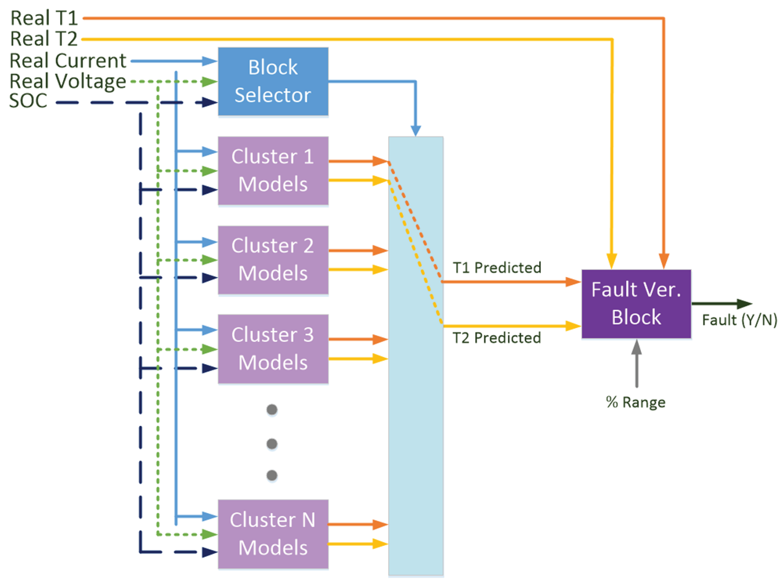

FIGURE 4. Model approach.

The final clustering will depend on the initial cluster centroids and on the value of K (number of clusters). Choosing K value is the most critical election because it requires certain prior knowledge of the number of clusters present in the data, which is highly doubtful. The K-means partitional clustering algorithm is computationally effective and works well if the data are close to its cluster, and the cluster is hyperspherical in shape and well separated in the hyperspace. As the final division depends on the initial cluster centroids, in order to create the best division, K-means algorithm should be used several times and the best division (in terms of distance between centroids) is chosen. The final centroids must be stored to assign new data to correct cluster.

3.1.2 Polynomial regression. Generally, a polynomial regression model [5] may also be defined as a linear summation of basis functions. The number of basis functions depends on the number of the model inputs, and the degree of the polynomial used.

With a degree 1, the linear summation could be defined as the one shown in equation (2). The model becomes more complex as the degree increases, equation (3) shows a second polynomial degree for the model

$$F(x) = a_0 + a_1 x_1 + a_2 x_2 \tag{2}$$

$$F(x) = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_1 x_2 + a_4 x_1^2 + a_5 x_2^2. \tag{3}$$

Despite that the polynomial regression technique is not an intelligent algorithm, it shows good performance against other more complex techniques when the dataset has a lot of variations. In this cases, polynomial regression usually obtain better MSE than other algorithms. However, the situation described before only happens with low order degree, when the degree of the polynomial increases, the complexity of the model increase, and in these cases, the intelligent techniques are better than this one.

3.1.3 ANNs: multilayer perceptron (MLP). ANNs has been successfully applied to solve real world problems [3, 9, 37, 38] An MLP is a feedforward ANN [5]. It is one of the most typical ANNs due to its robustness and relatively simple structure. However, the ANN architecture must be well selected to obtain good results.

The MLP is composed by one input layer, one or more hidden layers and one output layer, all of them made of neurons and with pondered connections between the neurons of each layer. Equation (4) shows the Tan-sigmoid function, a typical activation function used in ANNs, as Step, Linear and Log-sigmoid

$$F(t) = \frac{e^t - e^{-t}}{e^t + e^{-t}}. \tag{4}$$

3.1.4 Support vector regression (SVR), least square SVR (LS-SVR). SVR is based on the algorithm of the support vector machines (SVM) for classification. In SVR the main aim is mapping the data into a high-dimensional feature space F through a nonlinear plotting and doing linear regression in this space [40].

The least square algorithm of SVM is called LS-SVM. The solution estimation is obtained by solving a system of linear equations, and it is similar to SVM in terms of performance generalization [44]. The use of LS-SVM algorithm to regression is well known as LS-SVR [29]. In LS-SVR, the insensitive loss function is replace by a classical squared loss function, which makes the Lagrangian by solving a linear Karush–Kuhn–Tucker.

Although the SVM is used commonly in classification, this modification of the algorithm shows good performance in terms of error when the number of samples is sufficient. If the number of samples is low, its use is not recommended because it would cause over training and the model could not be used with new data.

3.2 Preprocessing the dataset

With the aim to achieve a good dataset, emphasize that it is necessary take into account full charging cycles of the battery. In order to achieve this fact, some incomplete cycles were discarded. Taken this fact into account, given that the whole data acquisition has twelve cycles, only nine cycles were included to calculate the model. The data were recorded with a sample time of one second, and with the explained discard, the dataset was reduced from 18130 to 16369 samples.

4 Results

The first technique applied to the dataset was clustering. To do that, K-means algorithm was applied and four clusters were created. To ensure the best clustering partition, the K-means algorithm was used with 20 replicates, with random initialization of the centroids; the final configuration is selected as the best of the 20 results obtained. These groups should represent the different states of the cell test.

Each model is obtained from the dataset by using K-Fold cross-validation, and then, the performance of each one was calculated.

The three mentioned regression techniques were trained for the four clusters, one by each output of the model. As an example, Figure 5 shows the temperature in sensor 2. The four colours indicate the different clusters, as it was mentioned above.

After K-means was applied, there was check the assignation of each data to the correct state of the test. All the data were verified, and the conclusion achieved is that there is no need to know the

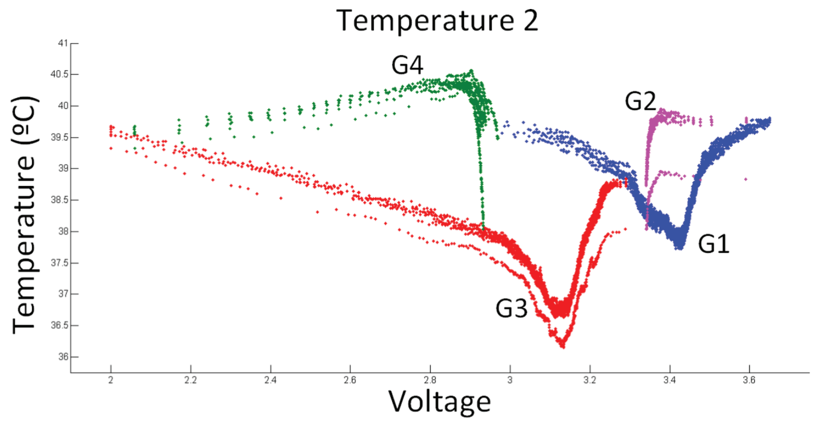

FIGURE 5. Temperature 2 vs. battery voltage.

state of the samples, with the centroids calculated with K-means is sufficient. Then, the regression techniques was applied for each cluster, and MSE is calculated. For it, it has been used 10 folds cross validation to ensure more general results than, for example, using hold out cross validation. With K-fold, all the data is used to train the model; for each cluster, 10 groups were created, and at the end of the validation, all the samples were used to train (9 times) and test (1 times each one).

The MLP-ANN regression algorithm was trained for different configurations. In all cases the topology uses one hidden layer, which number of neurons varies from 1 to 15. Its activation function is tan-sigmoid for all tests. However, the output layer neuron has a linear activation function. The used training algorithm was Levenberg–Marquardt with gradient descent, and its performance function was MSE.

The LS-SVR was trained with the self-tuning algorithm developed by KULeuven-ESAT-SCD and implemented in a MatLab toolbox. Due to that there are a lot of samples in some folds, the above algorithm was performed with 10% of the samples. With the achieved coefficients, then the model was created, but using all the available samples. The employed kernel was radial basis function, and the type was 'Function Estimation' for regression. The optimization function was 'simplex' and the cost-criterion 'leaveoneoutlssvm' with MSE as a performance function.

For polynomial regression, the order of the polynomial tested varies from 1st to 3rd order.

All the models were compared by using the MSE as the efficiency measurement. The testing data, as it was explained before, is all the data, but there were necessary 10 training cycles to collected all the testing data.

In Table 1 the lowest MSE and mean absolute error achieved for each group. It is also shown the algorithm and its configuration to achieved the best performance in every cluster.

It must take into account that the errors shown in Table 1 are the error in each cluster. For the global model, this error is the error for all the dataset, but in the hybrid model these errors only represent its own data. To perform a realistic comparative, it is possible to calculate a 'pondered' MSE that used the number of samples in each cluster to be calculated. This Hybrid MSE was $3.3445e-4$ for Temperature 1 and $3.3445e-4$ for Temperature 2.

It was a carry out validation of the completely fault detection model. To do that, 100 simulated faults have been created with temperatures out of the right operation range. As operation range, it has been considered the 5% out of the upper and the lower limit over the normal temperature. All the faults have been detected for the created model.

TABLE 1. Best errors for each cluster.

Variable	Cluster	Model	MSE	MAE
Temperature 1	Global	LS-SVR	$3.2956e-4$	0.0144
Temperature 1	(1)	ANN-MLP, 5 neurons	$3.6629e-4$	0.0150
Temperature 1	(2)	LS-SVR	$2.8433e-4$	0.0143
Temperature 1	(3)	ANN-MLP, 9 neurons	$3.1220e-4$	0.0139
Temperature 1	(4)	ANN-MLP, 8 neurons	$3.1842e-4$	0.0141
Temperature 2	Global	LS-SVR	$6.8033e-4$	0.0202
Temperature 2	(1)	LS-SVR	$7.2092e-4$	0.0206
Temperature 2	(2)	ANN-MLP, 3 neurons	$8.8523e-4$	0.0234
Temperature 2	(3)	LS-SVR	$6.0397e-4$	0.0192
Temperature 2	(4)	ANN-MLP, 3 neurons	$6.2507e-4$	0.0199

5 Conclusions

Very good results have been obtained in general terms with the novel approach proposed in this research. The final hybrid intelligent model implemented has different configuration for Temperature 1 and Temperature 2, that uses a combination of LS-SVR and ANN-MLP, depending on the cluster and the variable. Despite that the global model has better performance than some cluster, the final proposal is accomplished with local models after tested a combination of global and local models with the same data to demonstrate that global model had worst results.

The average MSE obtained with this implementation is $3.3445e-4$ for Temperature 1, and $3.3445e-4$ for Temperature 2. The maximum absolute error achieved was less than 0.025 degrees, and with this accuracy, the minimum steps recommended to set the range of fault detection is 1%, that should represent approximately 0.3 degrees for the real temperature.

It is remarkable that all the fault situations presented to the model was classify correctly as a battery fault; but as the model do not include the dynamic of the process, a bad measure could classify as battery fault two. This problem should be corrected in the next improve of the model, for example, taking into account that to detect a battery fault not only one measure should be out of range, or a minimum number of fails.

Moreover, in future works more complex testing for batteries should be collected, to ensure that all the possible situations are covered with the fault detection model.

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