

# 1     **Diagnosis of a battery energy storage system based on principal** 2                                     **component analysis**

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## 16    **Abstract**

17    This paper proposes the use of principal component analysis (PCA) for the state of health (SOH) diagnosis of  
18    a battery energy storage system (BESS) that is operating in a renewable energy laboratory located in Chocó,  
19    Colombia. The presented methodology allows the detection of false alarms during the operation of the BESS.  
20    The principal component analysis model is applied to a parameter set associated to the capacity, internal  
21    resistance and open circuit voltage of a battery energy storage system. The parameters are identified from  
22    experimental data collected daily. The PCA model retains the first 5 components that collect 80.25% of the  
23    total variability. During the test under real operation conditions, PCA diagnosed a degradation of state of  
24    health fastest than the commercial battery controller. A change in the charging modes lead to a battery recovery  
25    that was also monitored by the proposed algorithm, and control actions are proposed that lead the BESS to  
26    work in normal conditions.

27

28    **Keywords:** Diagnosis, battery energy storage system, principal component analysis, state of health.

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## 31    **1. Introduction**

32

33    Electricity service is of great importance for the development of a nation. However, more than 1.1 billion of  
34    the world's population is without access to electricity [1]. 85% of this population live in rural areas where  
35    carrying the interconnection of the electricity grid can be very expensive [1]. Some of these populations use  
36    diesel generators to face that problem. Nevertheless, market advances in renewable energies is leading to the  
37    replacement of these generators with stand-alone photovoltaic systems or hybrid renewable generators [2]. In  
38    these cases, the most used technology to store energy is battery energy storage systems (BESS). In off-grid  
39    applications, energy storage is a crucial component for ensuring reliability of these stand-alone renewable  
40    energy systems [3]. These systems primarily use lead acid batteries as a way to store electricity [4]. Besides,

41 this technology is low cost, mature and has efficient recycling processes [5]. Advances in lithium-ion  
42 technology are allowing this type of batteries to be used in renewable energy systems [6-8]. However, in 2015  
43 the lead acid battery market grew to \$37 billion [9, 10], so this technology is still being used as shown in the  
44 research developed in [11], and it will be working for long time.

45 During their operation, batteries are subjected to different charging and discharging processes, stress,  
46 temperature changes that affect their state of health (SOH). SOH reduction involves loss of capacity and an  
47 increase of internal resistance. SOH is used to know the conditions in which a battery has evolved from its  
48 start-up [12, 13], and it is generally defined in function of the current maximum capacity and its nominal  
49 capacity [14, 15]. Making a SOH diagnosis of the battery allows the operator to detect possible battery  
50 failures and to perform timely maintenance or replacement of the battery [16]. The study of the battery  
51 internal parameters opens a research field in order to make a better battery management system. Previous  
52 researches show different methods to identify the internal parameters of a battery [17-21]. These parameters  
53 are associated with the capacity, internal resistance and battery voltage. However, there are no previous  
54 research reports that analyze the evolution over time of these parameters and their relationship with battery  
55 SOH. This paper proposes the study of the internal parameters of a BESS and its evolution over time in order  
56 to generate useful information to perform SOH monitoring and diagnosis.

57 Because number of data to be managed is relatively high, it is very common in engineering to use a strategy to  
58 find correlation structures between the variables. One of these strategies is principal component analysis  
59 (PCA). According to [22, 23], PCA is a multivariate statistical process control technique that reduces the  
60 dimensionality of an original space that is established from the historical data of the measured variables to a  
61 space of lower dimensionality, searching linear combinations between the variables that best describe the  
62 process trend. PCA is based on the decomposition of the covariance matrix of the process variables along the  
63 directions that best explain the main causes of variability of the information analyzed [24-26].

64 In this paper a SOH diagnosis of a BESS is made by applying PCA to the internal parameters of a BESS. The  
65 methodology used to identify and extract the internal parameters of a BESS is explained in [17], and control  
66 actions are proposed that lead the BESS to work in normal conditions. The BESS has been working for three  
67 years during which data have been collected with a sampling time of 15 minutes, and is located in a renewable  
68 energy laboratory at Chocó – Colombia [27]. The BESS is composed of 24 Techno Sun 2V-OPzS-TCH2765  
69 ( $C_{10} = 2160$  Ah;  $C_{120} = 2765$  Ah) electrochemical accumulators connected in series. Regarding to Chocó  
70 department, it is considered as one of the rainiest regions in the world, with rainfall exceeding 9000 mm of  
71 annual precipitation and an average temperature of 27 °C. It is located in the western part of the country, in  
72 the region of the Pacific plain at 04° 00' 50'' and 08° 41' 3'' north latitude and 76° 02' 5'' and 77° 53' 3''  
73 west longitude. Chocó is a Colombian department with the largest number of municipalities with non-  
74 interconnected areas, where three-quarters of the department belong to rural areas with a rurality index  
75 between 43.65 and 73.67%. In the non-interconnected areas the electric power service is done through Diesel  
76 generators installed by the Institute for Planning and Promoting Energy Solutions for Non-Interconnected  
77 Zones (IPSE), with an operating time between 6 and 12 hours. In the rest of the Chocó, the electric power  
78 supply is made through the national interconnected system. This paper is organized as follows: Section 2  
79 describes the battery model used in this research. In Section 3 the PCA model is described and the  
80 mathematical foundations are indicated. The control actions carried out by the commercial controller are  
81 shown in Section 4. In Section 5 the PCA model is constructed and a diagnosis is made to new observations.  
82 Finally, the conclusions are presented in Section 6.

83

84

## 85 2. Methodology

### 86 2.1. Overview

87 To carry out this diagnosis, we first used the battery model developed by Copetti [18] to represent the voltage  
88 and the state of charge of the BESS. Then we identify the BESS internal parameters by using particle swarm  
89 optimization (PSO) algorithm and are explained in [17].

### 90 2.2. PSO algorithm description

91 PSO is an evolutionary computation technique that emulates animal behavior through particles with certain  
92 position and velocity in a search space, where the population is called swarm, and each member of the swarm  
93 is called a particle. In PSO, each of the particles retains the record of the location of the best particle that  
94 provides the position/location value and is denoted  $pbest$  [28-29]. After collecting the pbest information for  
95 each particle the algorithm uses these values to find the optimal global solution that is denoted by  $gbest$  [28-  
96 29]. However, despite the similarity with other heuristic techniques such as genetic algorithms (GA), PSO  
97 does not imply mutation and crossover function. PSO finds the best global solution by adjusting the  
98 movement vector of each particle according to its personal best position (cognitive aspect, second term) and  
99 the best global position (social aspect, third term) of the particles in the whole swarm in each iteration.

100 The first term is only the current velocity of the particle and can be considered as an impulse term. The  
101 second term that is associated with a local search is proportional to the vector  $(pbest_i^k - x_i^k)$  and points from  
102 the current position of the particle to its best personal position. The third term that is associated with a global  
103 search is proportional to  $(gbest^k - x_i^k)$  and points to the position of the best global particle [29-31].

104

$$v_i^{k+1} = \omega \cdot v_i^k + c_1 r_1 (pbest_i^k - x_i^k) + c_2 r_2 (gbest^k - x_i^k) \quad (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

105

106 Where,  $r_1$  and  $r_2$  are random numbers in the range [0, 1].  $k$  is the current number of iterations.  $\omega$  is known as  
107 the inertial constant or inertial weight and its recommended value is slightly less than 1 (a non-negative  
108 number) which regulates the search range of the solution space.  $c_1$  and  $c_2$  are the acceleration constants that  
109 determine the amount of particles directed towards an ideal position. One of them is called the cognitive  
110 component and the other is designated as a social component. The significance of these two constants is that  
111 they determine to what extent pbest and gbest affect the movement of the particles. The recommended value  
112 for these two constants is approximately 2 [30-32].

113 To the identified parameters a PCA model is applied and the causes that are affecting the model are identified.  
114 Finally, control actions are proposed that lead the BESS to work in normal conditions.

### 115 2.3. The model

116 The model developed by Copetti [18] can be used to describe the dynamics of a BESS. The state of charge  
117 (SOC) and the battery capacity can be computed the next three equations:

$$SOC(t) = SOC_0 - \frac{1}{C(t)} \int_0^t \eta_c I(t) dt \quad (3)$$

118

$$C(t) = \frac{C_N \times C_{icoef} \times k_{c10}}{1 + A_{cap} \left( \frac{|I(t)|}{I_N} \right)^{B_{cap}}} (1 + \alpha_c \Delta T + \beta_c \Delta T^2) \quad (4)$$

119

$$I_N = \frac{C_N}{m} \quad (5)$$

120

121 Where  $\beta_c = 0$  °C;  $\Delta T = T - T_{ref}$  is the battery temperature variation regarding to a reference temperature ( $T_{ref}$   
 122 = 25 °C);  $I_N$  is the battery nominal current;  $C_N$  is the battery nominal capacity (at  $m$  hours);  $0 \leq SOC(t) \leq 1$ ,  
 123  $C_{icoef}$ ,  $A_{cap}$  and  $B_{cap}$  are empirical parameters, and  $k_{c10}$  is the battery capacity reduction coefficient.

124 The battery internal resistance is expressed by equations (6) and (7)

$$R_{int}(T) = \frac{n_s}{C_N} (R_1 + R_2 + R_3) (1 - \alpha_r \Delta T(t)) \quad (6)$$

125

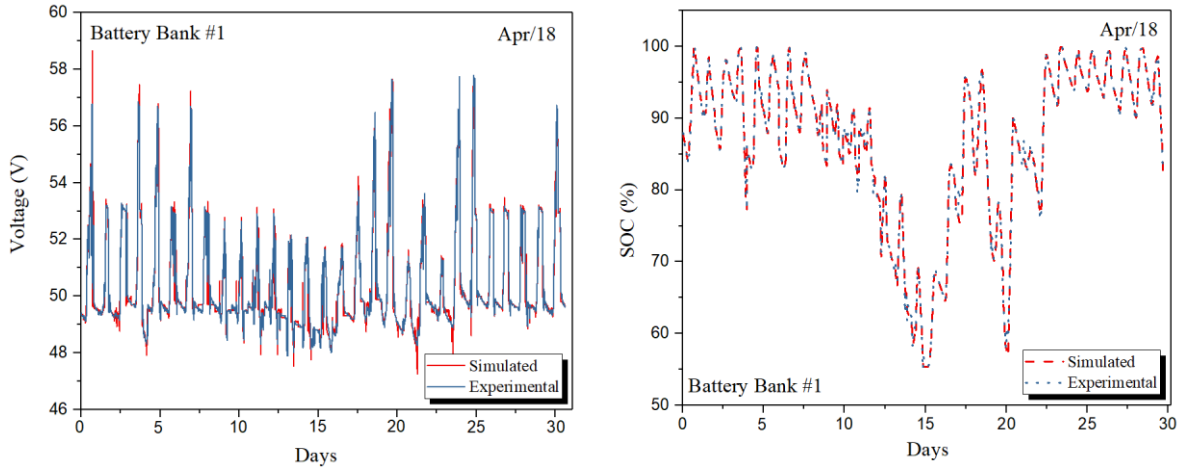
$$R_{int}(T) = \frac{n_s}{C_N} \left( \frac{P_1}{1 + |I_{bat}(t)|^{P_2}} + \frac{P_3}{(1 - SOC(t))^{P_4}} + P_5 \right) (1 - \alpha_r \Delta T(t)) \quad (7)$$

126

127 Where,  $R_1$  and  $R_2$  represent the influence of the charge/discharge current  $I_{bat}$ ,  $R_3$  represents the Ohmic effect  
 128 [33], and  $n_s$  is the number of connected batteries in series.  $P_{1dc}$ ,  $P_{2dc}$ ,  $P_{3dc}$ ,  $P_{4dc}$ , and  $P_{5dc}$  are parameters related  
 129 to resistive losses [19]. Discharging and charging voltages can be described by equations (8) and (9). These  
 130 equations were taken from [17].

$$V_{dc}(t) = n_s [V_{bodc} - K_{bodc} (1 - SOC(t))] - n_s \frac{|I_{bat}(t)|}{C_{10}} \times \left( \frac{P_{1dc}}{1 + |I_{bat}(t)|^{P_{2dc}}} + \frac{P_{3dc}}{SOC(t)^{P_{4dc}}} + P_{5dc} \right) \times (1 - \alpha_{rdc} \Delta T(t)) \quad (8)$$

$$V_c(t) = n_s [V_{boc} + K_{boc} (SOC(t))] + n_s \frac{|I_{bat}(t)|}{C_{10}} \times \left( \frac{P_{1c}}{1 + |I_{bat}(t)|^{P_{2c}}} + \frac{P_{3c}}{(1 - SOC(t))^{P_{4c}}} + P_{5c} \right) \times (1 - \alpha_{rc} \Delta T(t)) \quad (9)$$



133 Figure 1. BESS voltage, SOC measurements, and simulation results. Case study: BESS located in the  
 134 renewable energy laboratory at Chocó – Colombia. BESS voltage signals (left), and BESS SOC signals  
 135 (right).

136

137 In order to use the model, each parameter can be fitted to represent the real behavior of the system. To  
 138 identify the internal parameters of the BESS we use the methodology presented in [17]. In [17], an  
 139 improvement of the PSO algorithm is used to fit the data and the results show an accurate response of the  
 140 model as it is shown in Figure 1. As [17] have already proved the effectiveness of the method, this paper does  
 141 not give more details about parameter identification.

142 The identified parameter set for each day is the initial data to perform the SOH diagnosis of the lead acid  
 143 BESS by PCA.

144

### 145 3. Principal component analysis (PCA)

146

147 PCA is a technique used to reduce the dimensionality of a data set that tries to lose as little information as  
 148 possible [23, 34]. PCA allows determining differences between samples, which are the variables that  
 149 contribute most to differentiate the samples and detect correlations between variables. When a PCA is  
 150 applied, a new system variable called principal component (PC) is generated. The first PC contains most of  
 151 the information contained in the original data matrix; the second PC provides a maximum of the resulting  
 152 residual variance, and so on [35, 36]. PCA results can be represented in "scores" and "loadings" charts [37].  
 153 The scores chart represents the differences and the similarities between samples and it is used to find clusters  
 154 between them. The loadings chart determines the correlation between variables. The univariate representation  
 155 of the loading  $p_a$  contributes to identify the variables of greatest influence on each PC and to associate a  
 156 practical interpretation for the components. Through a bivariate loadings chart ( $p_a$  vs  $p_{a'}$ ) a partial  
 157 representation of the usual correlation structure between the variables of the original matrix  $X$  is obtained. In  
 158 this representation, the location of the variables in the same direction and away from the origin is an indicator  
 159 of positive correlation. Conversely, its location in the opposite direction indicates negative correlation.  
 160 Variable groups with low correlation will be located in perpendicular directions, distant from the origin. The  
 161 similarity between the  $X$  records can be evaluated through bivariate charts of the score ( $t_a$  vs  $t_{a'}$ ). Average  
 162 individuals will be located in the chart center, while the eccentric individuals are the most contributing  
 163 individuals for each PC.

164 **3.1. Practical application of PCA**

165 To monitor a multivariate system such as the internal parameter set of a BESS, it is essential to know widely  
 166 its habitual behavior and the correlation structure between its variables. These elements can be characterized  
 167 using data collected during a reference period (Phase I) in which the system has worked under the regular or  
 168 desired condition. Data collected on Phase I, are used to adjust a statistical model that reproduces the habitual  
 169 behavior of the BESS. Later, in Phase II, the Phase I model is used to evaluate the concordance of future  
 170 observations. In PCA, the observation matrix  $X$  (Eq. (10)) is decomposed into a set of  $A$  ( $A < \text{rank}(X)$ )  
 171 matrices of rank 1 [38].

172

$$X = \sum_{a=1}^A t_a * p_a^T + \sum_{a=A+1}^{\text{rank}(X)} t_a * p_a^T = T * P^T + E \quad (10)$$

173

174  $P \in R^{K \times A}$  is the loading matrix composed of the eigenvectors ( $p_a$ ) associated with the highest  $A$  values ( $\lambda_a$ ) of  
 175 the covariance matrix of  $X$ .  $K$  indicates the number of variables;  $A$  is the number of principal components, and  
 176  $N$  indicates the number of samples. Vectors  $p_a$  ( $a = 1, 2, \dots, A$ ) contain the coefficients of the original variables  
 177 of  $X$  in the principal components (PCs) and define the  $A$  directions of highest variability.  $T \in R^{N \times A}$  is the score  
 178 matrix, which contains the location of the projections of the rows of  $X$  over the  $A$ -dimensional subspace ( $T =$   
 179  $XP$ ). Each column of  $T$  is a vector  $t_a$  ( $a = 1, 2, \dots, A$ ), which represents the  $a$ th PC. The matrix  $E \in R^{N \times K}$  stores  
 180 the residuals obtained by predicting  $X$  from  $T * P^T$  ( $E = X - T * P^T$ ). So,  $E$  (residual matrix) contains the  
 181 information of  $X$  that is not explained by the PCA model.

182 PCA is a scale-dependent technique therefore the results of the PCA can vary significantly depending on the  
 183 scale of measurement of the variables. In multivariate monitoring it is very frequent that the scales of the  
 184 variables are notoriously different, for which it is necessary to perform a previous work of scaling the  
 185 columns of the matrix  $X$ . A very common procedure is to standardize (center with respect to your average and  
 186 scale by the standard deviation) each of the columns of the matrix  $X$ . With this preprocessing, all variables are  
 187 expected to have the same weight in the construction of the PCA model. It is also common to find that the  
 188 data matrix  $X$  is made up of small subsets or blocks of variables, each of which contains information about a  
 189 particular feature of the system. In these cases, the contribution of each block of variables can be leveled out  
 190 through a scaling procedure per block. In this preprocessing each variable ( $X_{.j}$ ) is centered with respect to its  
 191 average value ( $\bar{X}_{.j}$ ), and scaled by the product between its standard deviation ( $S_{.j}$ ) and the square root of the  
 192 number of parameters ( $\sqrt{K_h}$ ) that make up the  $h$ -th block (to which the variable belongs). This scaling is  
 193 represented in equation (11). A matrix of transformed data ( $X^*$ ) is generated with this procedure in which  
 194 each block of parameters provides the same level of variability.

$$X_{.j}^* = \frac{X_{.j} - \bar{X}_{.j}}{\sqrt{K_h} * S_{.j}} \quad (11)$$

195 In the construction of the PCA model, the user must decide the number of PCs ( $A$ ) that there will be used for  
 196 the analysis. In order to determine this number, a quality criterion for representing the data in the new  
 197 subspace is generally used. One of the most used criteria is the cumulative percentage of variance (CPV) [39]  
 198 (Eq. (12)) explained by the model.

$$CPV(A) = \frac{\sum_{a=1}^A \lambda_a}{\sum_{a=1}^{rank(X)} \lambda_a} 100\% \quad (12)$$

199 Once the  $A$  components are selected, the elements of the PCA model ( $T, P, E$ ) are used to understand the PCs  
 200 system, to study the correlation between the variables of  $X$ , to evaluate the similarity between the records and  
 201 to identify extreme observations in the reference data set. The extreme observations identification is made  
 202 using the information contained in the score matrix ( $T$ ) and in the residuals matrix ( $E$ ). The PCA model  
 203 transforms each observation (row) of the matrix  $X^*$ ,  $x_i = (x_{i1}, x_{i2}, \dots, x_{ik})$  into a projections vector in PCs  $t_i =$   
 204  $(t_{i1}, t_{i2}, \dots, t_{iA})$ , and a residue vector  $e_i = (e_{i1}, e_{i2}, \dots, e_{ik})$ . This pair of vectors are summarized in two  
 205 independent statistics: Hotelling's  $T^2$  (Eq.(13)) and sum of square prediction error (SPE) (Eq. (14)).

$$T_i^2 = t_i^T \Theta^{-1} t_i = \sum_{a=1}^A \frac{t_{ia}^2}{\lambda_a} \quad (13)$$

206

$$SPE_i = e_i^T * e_i = \sum_{j=1}^K e_{ij}^2 \quad (14)$$

207 Where  $\Theta = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_A)$  is the diagonal matrix of the  $A$  eigenvalues associated with the PC retained in  
 208 the PCA model. Under the assumption that the score vector follows a multivariate normal distribution, a  
 209 upper control limit (UCL) greater than  $(1-\alpha)\%$  for the  $T^2$  statistic can be set at (Eq. (15)):

$$UCL_{T^2} = \frac{(N^2-1)A}{(N-A)N} F_{\alpha, A, N-A} \quad (15)$$

210 Where  $F_{\alpha, A, N-A}$  is the critical value of a random variable of the  $F$  (Fisher-Snedecor) distribution, with  $A$   
 211 degrees of freedom in the numerator and  $N - A$  degrees of freedom in the denominator, and  $\alpha$  is the level of  
 212 significance [27, 39, 40]. Zhao et al. [41] suggests setting the control limit for the SPE statistic on the critical  
 213 value of a weighted chi-squared distribution ( $g\chi_h^2$ ). Where  $g$  is the weight and  $h$  is the degrees of freedom.  
 214 Nomikos et al. [42] suggest to approximate the value of the degrees of freedom  $h$  and of the weighting  $g$ ,  
 215 equaling the mean and the variance of the  $g\chi_h^2$  distribution with the sampling average ( $m$ ) and the sampling  
 216 variance ( $v$ ) of the SPE statistic in the observations of Phase I. Therefore the control limit to  $(1 - \alpha) \%$  for SPE  
 217 can be set as (Eq. (16)):

$$UCL(SPE) = \frac{v}{2m} \chi_{\frac{2m^2}{v}, \alpha}^2 \quad (16)$$

218 Where,  $g = v/2m$  and  $h = 2m^2/v$

219  $T^2$  and SPE are calculated for each row of the matrix  $X^*$  and they are plotted together with the control limits.  
 220 These two statistics contain complementary information to identify extreme observations in the data set.  
 221 However, their interpretation is notably different. A point that is signaled by the statistic  $T^2$  corresponds to an  
 222 observation whose projections in the space of the components are very extreme. This means that this  
 223 observation has an abnormal value in one or more of the variables, but maintains the direction of the usual  
 224 correlation structure. In the PCA model this point is labeled as an extreme observation. Besides, a point that is  
 225 indicated by the SPE statistic corresponds to an observation whose prognosis through the PCA model is  
 226 significantly different from its observed value. In this case, one or more of the variables have an abnormal

227 value that does not correspond to the usual correlation structure. This point is labeled as extreme observation  
 228 outside the PCA model. The presence of these extreme points can significantly condition the results obtained  
 229 in the PCA model. Therefore, when they are identified in phase I it is convenient to remove them from the  
 230 observation matrix and adjust the model again. In phase II, the final PCA model of phase I is used to monitor  
 231 new observations of the process. In this phase, each new multivariate observation  $x_{new}$  is projected on the  
 232 subspace of the PC. Then, the score vector ( $t_{new} = x_{new}P$ ) and the forecast error vector  $e_{new} = x_{new} - t_{new}P^T$  are  
 233 calculated. With that information, both SPE and Hotelling's  $T^2$  statistics are calculated and the observation is  
 234 represented in the two control charts. If some of the two statistics exceed the control limit, a change signal is  
 235 generated and the variable involved in the change must be identified. In the monitoring of multivariate  
 236 processes, contribution plots are one of the most used tools to diagnose the variables associated with a signal  
 237 of change. When the observation is indicated by the SPE chart, the contribution of the variable  $j = 1, 2, \dots, K$ ,  
 238 on the SPE statistic, corresponds to the square of its forecast error (the error sign is retained to facilitate the  
 239 interpretation), as it's shown in Eq. (17):

$$C_j^{SPE} = sign(e_{new,j}) * e_{new,j}^2 \quad (17)$$

240 If the observation is indicated by the  $T^2$  statistic, then the contribution of variable  $j$  to the  $T^2$  statistic is  
 241 calculated as (Eq. (18)):

$$C_j^{T^2} = \sum_{a=1}^A \frac{t_{new,a} *_{new,j} * p_{j,a}}{\lambda_a} \quad (18)$$

242 Therefore, those variables with the greatest contribution to the statistic can be identified as potential cause of  
 243 the signal disturbance. In addition to the Hotelling's  $T^2$ , SPE and contribution plots, the graphical  
 244 representation of the projection of the new observations in the space of each PC, together with the bivariate  
 245 loadings plots are very useful to identify the extreme observations and the possible associated variables that  
 246 cause the problem.

247

#### 248 4. Controller actions

249 A commercial controller carries out the battery management: Sunny Island™ inverter. The controller applies  
 250 a charging strategy (boost, full, float or equalization) that will depend on the SOC and the configuration of the  
 251 battery. Figure 2, shows the different Sunny Island™ charging phases. In boost charge and full charge mode a  
 252 charging voltage of 2.4 V is applied to the BESS cells, meanwhile in float charge and equalization charge  
 253 mode a voltage of 2.25 V and 2.5 V respectively is applied to the BESS cells.



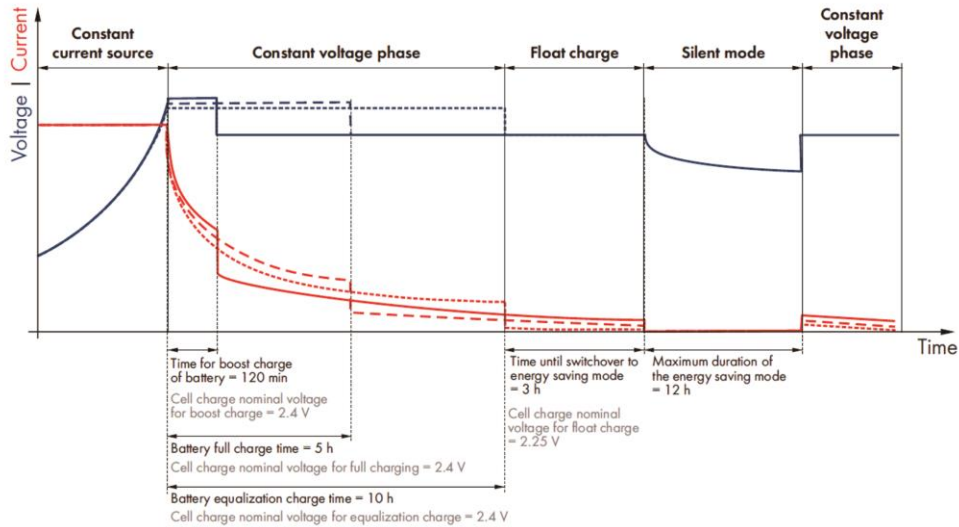
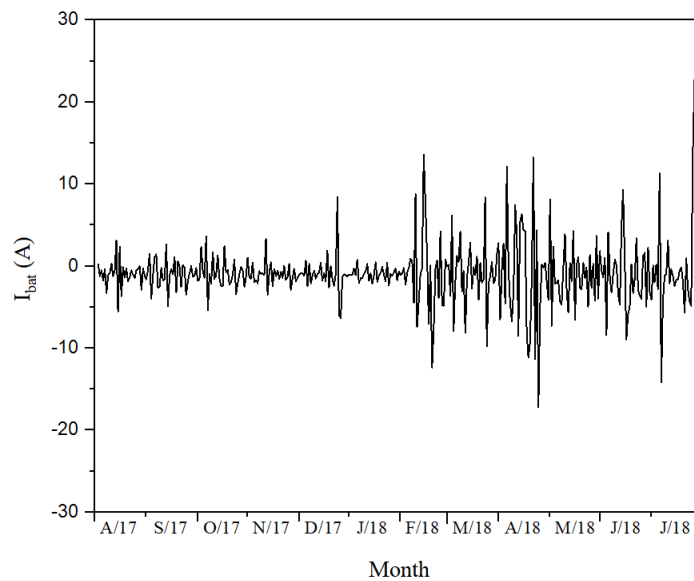


Figure 2. Sunny Island™ inverter charging phases for an AGM battery [43].

254  
255  
256

257 When the BESS operates under normal conditions, the controller maintains a float charge. However, due to  
258 different operating conditions, the controller can use other charging modes more aggressive: boost charge, full  
259 charge, or equalization charge. The different charging modes that the BESS experiences can lead to an  
260 increase in the current (see Figure 3), and therefore an increase in battery temperature. This increase in current  
261 and temperature can lead to a premature deterioration of the battery.



262

263 Figure 3. One-year measurements of BESS current taken from the renewable energy laboratory at Chocó –  
264 Colombia.  
265

266 Taking into account this abnormal behavior of the BESS current, we proceed to make a diagnosis by PCA,  
267 find the possible causes and propose solutions that lead the BESS to work under normal conditions.

268

269 **5. Application of PCA to BESS.**  
 270 **5.1. Phase I: Construction of the PCA model**

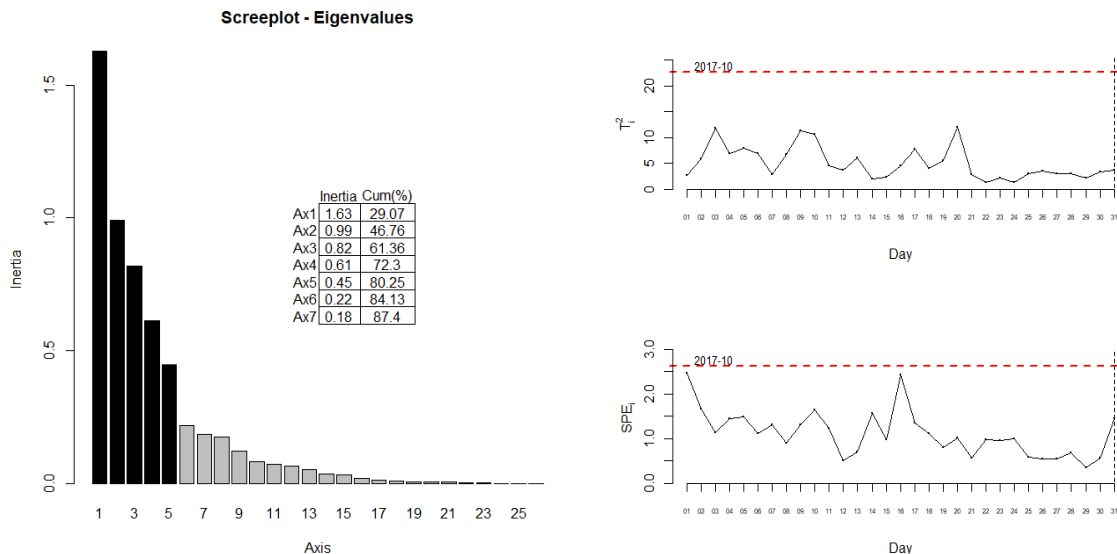
271 The characterization of the normal behavior of the internal parameters of the BESS is carried out through a  
 272 PCA model. As reference data, the daily identifications of the model parameters corresponding to the month  
 273 of October 2017 (31 records) are used. Each record contains the identification of 13 parameters for the  
 274 charging equations and other 13 for the discharging equations of the BESS. These parameters are grouped  
 275 into three blocks, depending on their relationship with key features of BESS. Table 1 presents the definition  
 276 of the parameters considered and the related feature<sup>1</sup>.

277 Table 1. Parameters considered for the diagnosis of the BESS.

Parameters	Feature/Block
$P_1, P_2, P_3, P_4, P_5, \alpha_r$	Internal Resistance
$C_{lcoef}, A_{cap}, B_{cap}, \alpha_c, K_{c10}$	Capacity
$V_{boc}, K_{boc}$	Open circuit voltage

278 So, the set of reference data ( $X$ ) corresponds to a matrix of 31 registers and 26 parameters that have to relate  
 279 to the BESS SOH. In this initial matrix each parameter has its own scale of measurement. Additionally, as  
 280 Table 1 shows, the number of parameters that make up each block is not homogeneous. Therefore, there is an  
 281 imbalance in the contribution of each block of parameters on the total variability of the reference data matrix.  
 282 To level the contribution of each block on the total variability, a scaling procedure (as the one described in  
 283 section 2) is performed per block. With the preprocessed data matrix ( $X^*$ ), a first PCA model is built, whose  
 284 goal is to verify the stability of the reference data and to identify atypical or influential points in the PCA  
 285 model.  
 286

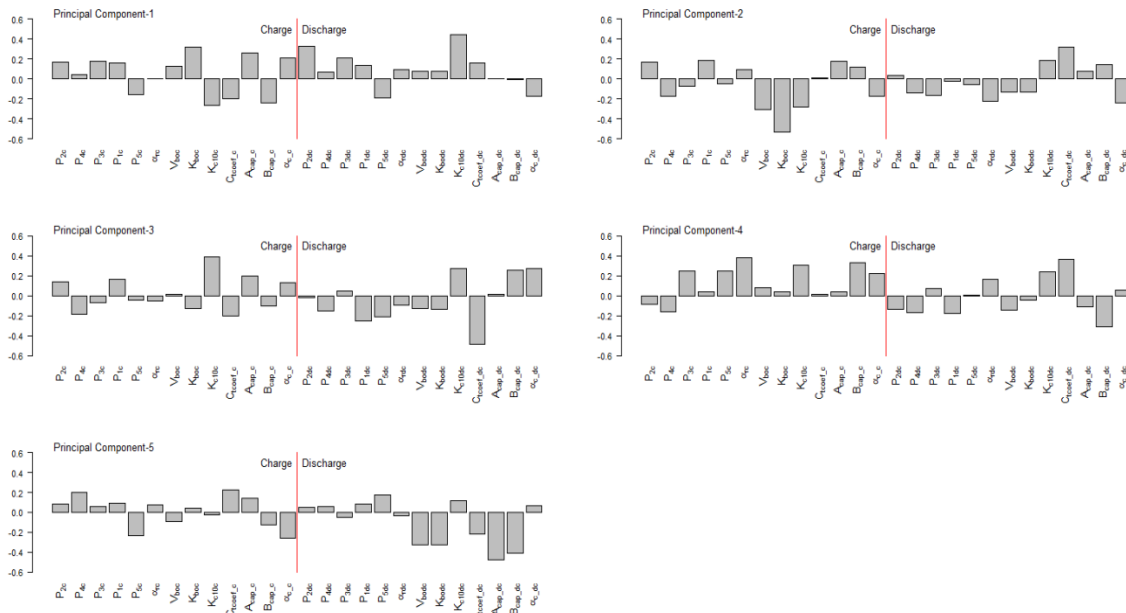
287 Hotelling's  $T^2$  and SPE control charts, with control limits established under a 1% level of significance are  
 288 used for the diagnosis of observations. As shown in Figure 4. a), the first 5 PCs retain 80.25% of the total  
 289 variability. Atypical or influential observations are not presented in the reference data set (see Figure 4b)).



290 Figure 4. a) Plot of the final PCA model. b) Hotelling's  $T^2$  and SPE control charts for the filtered reference  
 291 data.  
 292  
 293

<sup>1</sup> Note that each parameter has a value for the charging process and other for the discharging process.

294 The set of PC makes up a set of indicators of the BESS SOH. They are computed from the information  
 295 contained in the parameters weighted according to the coefficients illustrated in Figure 5. In each state  
 296 (charging and discharging) of the BESS the parameters that have more weight are:  $K_{boc}$ ,  $K_{c10}$ ,  $C_{lcoef}$ ,  $A_{cap}$ ,  $B_{cap}$ .  
 297 When working with 5 PCs, each parameter evolves over a 5-dimensional space and it is usual to use the  
 298 projections over each 2-dimensional subspace to show the evolution. Therefore, 5 PC, 10 PC combinations are  
 299 generated (1-2, 1-3, 1-4, 1-5, 2-3, 2-4, 2-5, 3-4, 3-5, 4-5) with the same number of charts.



300

Figure 5. Coefficients (loadings) of the parameters in each PC.

301

302

303

## 5.2. Phase II - Diagnosis of new observations.

304

The PCA model identified at phase I is used to diagnose new observations of the internal parameters of the BESS. Figure 6 illustrates the diagnosis algorithm flow. Each day, a set of new observations are organized in a  $X_{new}$  data matrix, whose columns receive the same transformation as in Eq. (10). Then, Hotelling's  $T^2$  (where  $i$  stand for the day) is computed for this data set and it is monitored with a control chart.

308

Note that Y axis of the Hotelling's  $T^2$  control chart determines the similarity between two multidimensional random variables, i.e. is the distance (Mahalanobis distance) of the new data with respect to the original model. The difference with the Euclidean distance is that Mahalanobis distance takes into account the correlation between the random variables. The Hotelling's  $T^2$  control chart with control limits is presented in Figure 7. In order to monitor the alarm degree, this paper proposes splitting Hotelling's  $T^2$  control chart into two regions: Level 0 (no alarm), and alarm level 1. Below the established control limit (1% false alarm rate), the BESS is assumed to operate under normal conditions. At alarm level 1, the system still shows good performance but its performance does not match the training conditions. However, when the difference greater than  $\delta T^2$  then, the system working outside its normal conditions. Therefore, if new data in Hotelling's  $T^2$  are placed on level 0, the system is working normally. When there are 3 or more consecutive points and uprising trends on alarm level 1, it means that the identified parameters are different enough from the original ones. Therefore, the diagnosis procedure starts. The complete diagnosis of the situation requires the analysis of the parameters causing the alarm. Therefore, after the diagnosis of the alarm zone, the contribution of each parameter to Hotelling's  $T^2$  has to be studied.

321

322 If the points are located in an alarm zone, then inputs have to be checked. If there are abnormal weather  
323 conditions or an abnormal demand, then the training conditions are extremely different to the current ones so  
324 it is not possible to conclude that there is or not a failure. So, no action is required.

325

326 i. If external conditions are similar from the PCA training month, and the alarm signal is generated  
327 by  $C_{icoef}$ ,  $A_{cap}$ ,  $B_{cap}$ ,  $\alpha_c$ ,  $K_{c10}$  parameters then the battery is entering a process of loss of capacity  
328 that may be due to: low electrolyte level, electrolyte stratification, low levels of SOC, shedding,  
329 sulfation, or degradation of the active matter, all associated with the degradation of battery.

330

331 Check the electrolyte level: If the level is low, then fills with distilled water to the level recommended by the  
332 manufacturer and verify that the specific density of each cell is that specified by the manufacturer (between  
333  $1.265 \pm 0.50$  Kg/l to 25 °C). Apply a full charge (full charge time = 5 h). The goal is to charge the battery  
334 until it reaches a SOC > 90%. When the battery is charged, apply an equalization charge (equalization charge  
335 time = 10 h) to compensate for the differences that may occur in the SOC of the battery cells and finally  
336 change float charge mode. If after applying this procedure the battery capacity is recovered, and  $T^2 < 3.2$ , then  
337 the system works in normal conditions, therefore change to float charge mode. If the electrolyte level is not  
338 low, then check the SOC. If the SOC is between 70% and 80% then apply a boost charge until the battery  
339 reaches 85% and 90% of its current capacity (time for boost charge of battery = 2 h). Then perform a full  
340 charge (full charge time = 5 h) until the SOC > 90%. If the capacity is recovered, then the system works under  
341 normal conditions, therefore change to float charge mode. If the SOC > 80% then, apply an equalization  
342 charge (equalization charge time = 10 h). If the battery capacity is recovered, then the system works under  
343 normal conditions, therefore change to float charge mode.

344 If after applying all these procedures the battery capacity is not recovered, then the battery has a failure that  
345 can be due to detachment of active material from the electrodes (shedding), sulphation or degradation of the  
346 active matter, among others, that they can not be recovered with controller actions. Therefore the battery must  
347 be brought to maintenance or in its effect; it must be replaced by another of the same feature.

348

349 ii. If the alarm signal is generated by  $P_1$ ,  $P_2$ ,  $P_3$ ,  $P_4$ ,  $P_5$ ,  $\alpha_r$  parameters then the battery is presenting  
350 resistive losses that are associated with prolonged operating conditions at very low SOC that  
351 lead to degradation processes such as corrosion, generating an increase in internal resistance and  
352 therefore an increased risk of failure.

353

354 Check the SOC: If the SOC is very low, i.e., SOC < 60%, then apply a boost charge until the battery is  
355 between 85% and 90% of its current capacity (time for boost charge of battery = 3 h). Then change from  
356 boost charge to full charge (full charge time = 5 h). Once the battery is charged, perform an equalization  
357 charge (charge equalization time = 10 h). If after applying this procedure the battery internal resistance  
358 decreases, then the system works in normal conditions, therefore change to float charge mode. If SOC > 60%,  
359 apply a boost charge until the battery is between 85% and 90% of its current capacity (time for boost charge  
360 of battery = 2 h). Then change from boost charge mode to full charge (full charge time = 5 h). If the battery  
361 internal resistance decreases, then the system works under normal conditions, therefore change to float charge  
362 mode. If after applying these procedures the internal resistance does not decrease, then the battery has a fault  
363 that it can not recover with controller actions. Therefore, the battery must be replaced by another with the  
364 same feature.

365

366 iii. If the alarm signal is generated by the  $V_{boc}$ ,  $K_{boc}$  parameters, then is a cause of battery failure and  
367 can not be recovered with controller actions. Therefore the battery must be brought to  
368 maintenance or in its effect; it must be replaced by another of the same feature. If the open  
369 circuit voltage parameters are inside range, then the system works under normal conditions,  
370 therefore change to float charge mode.

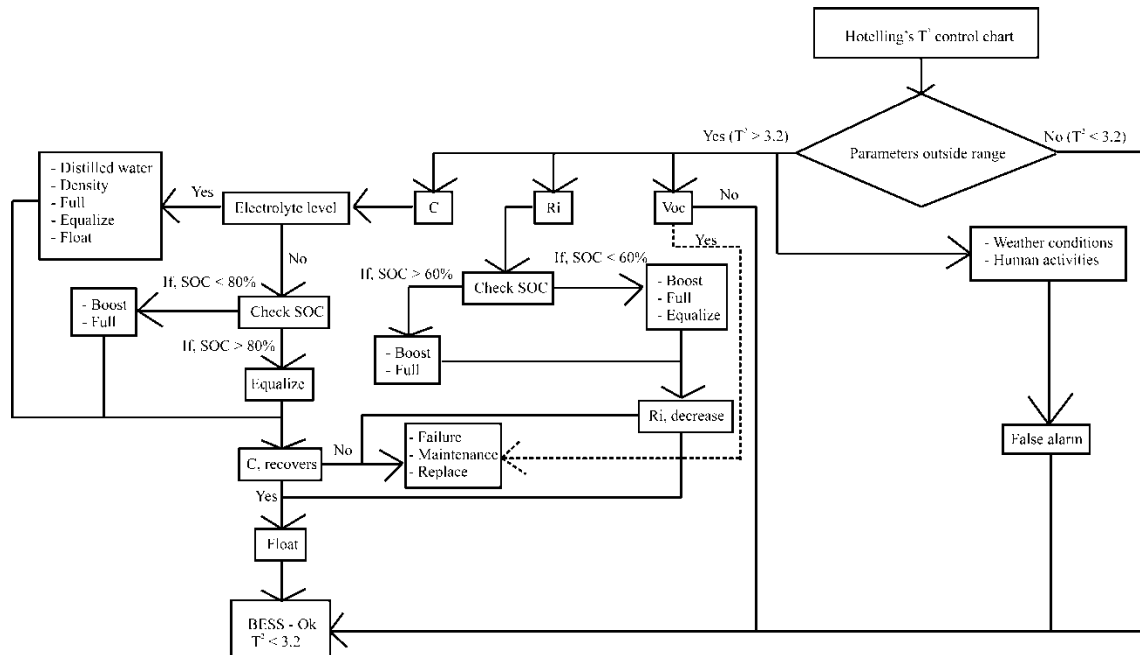


Figure 6. Flow chart of Hotelling's  $T^2$  control chart

371  
372  
373

374 To illustrate the procedure, monitoring is initially performed for the month of November 2017 (see Figure 7).  
375 A logarithmic scale is used for a better visualization of  $T^2$  progress. The higher the value of  $T^2$ , the greater the  
376 distance between the observation and the target value.

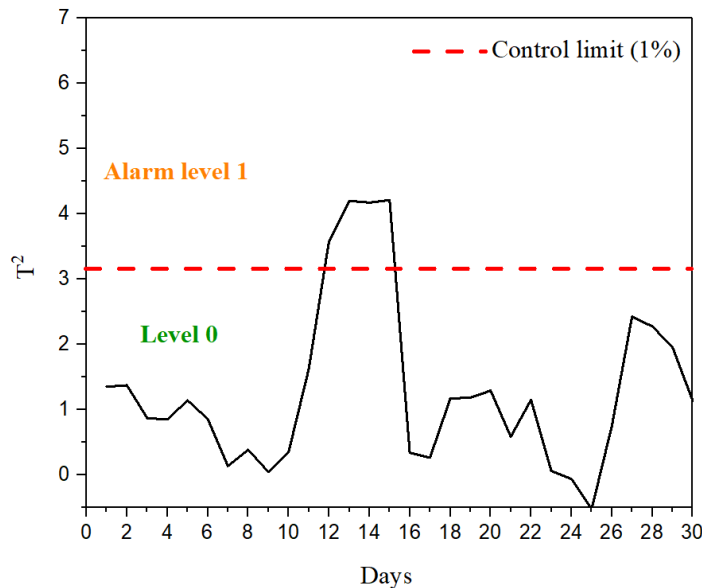
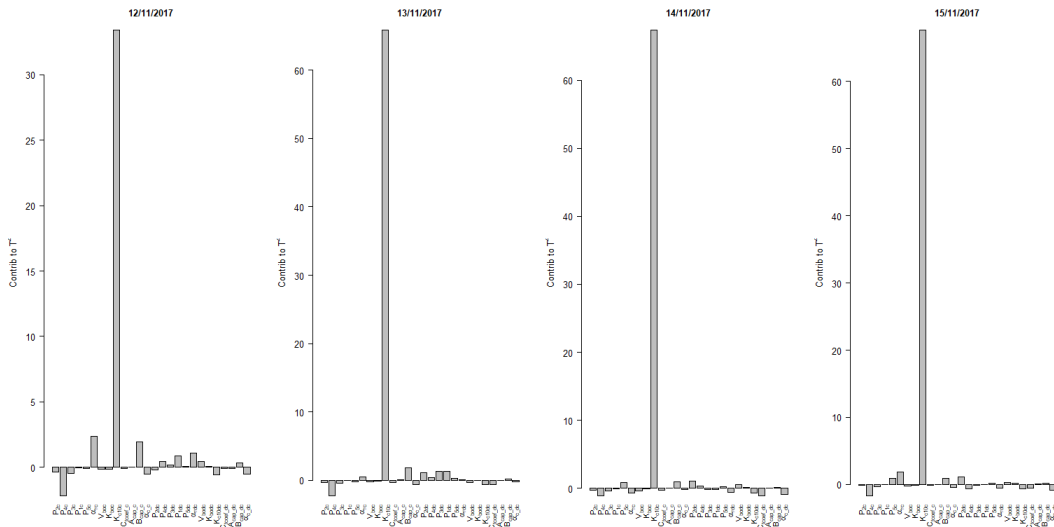


Figure 7. Hotelling's  $T^2$  for November 2017 monitoring.

377  
378  
379

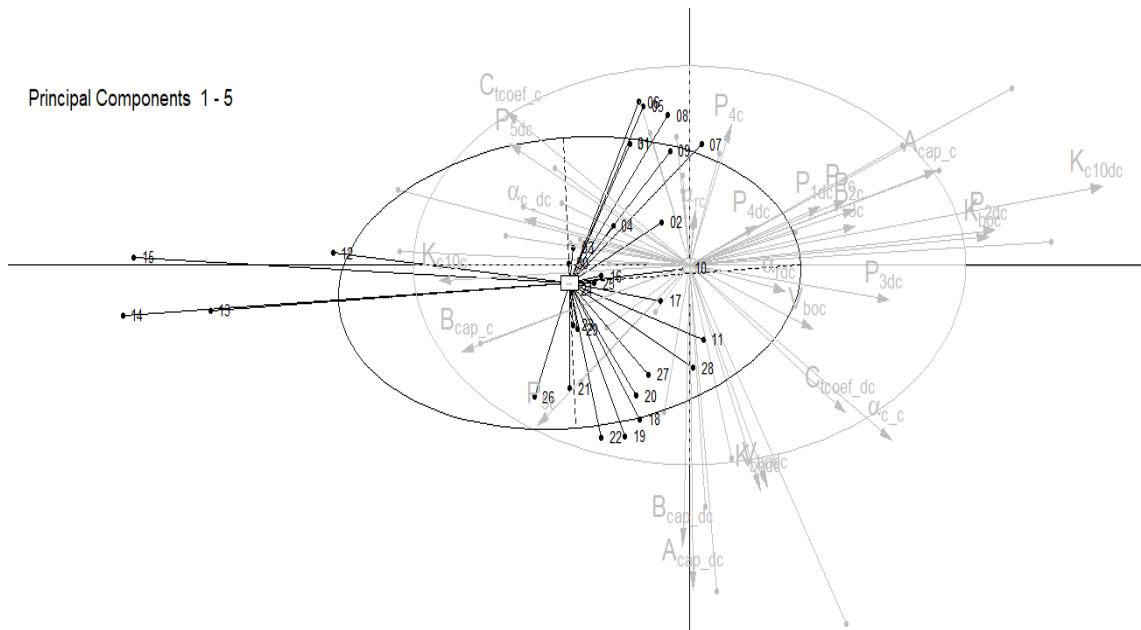
380 According to the diagnosis, the system exhibits unusual behavior on days 12 to 15 and inside the PCA model  
381 for the rest of days. Therefore, the next step should be the identification of the variables that have caused the  
382 unusual behavior and, then, try to explain this abnormal behavior. This analysis can be done by observing the  
383 contribution plots or by analysing the projections of the observations in the space of the principal components.

384 Figure 8 shows the contributions plots to the Hotelling's  $T^2$  obtained for the alarms generated on November  
 385 12 to 15, 2017.



386  
 387 Figure 8. Contribution plots to the Hotelling's  $T^2$  of the extreme observations within the PCA model.  
 388

389 According to this chart, there was an unusual increase in the  $K_{c10}$  parameter in the charge phase of BESS  
 390 during four days. This parameter was included in the model for the first time in [17] and it allows to adjust the  
 391 battery model proposed in [18] reaching a lower measurement error between the experimental and simulated  
 392 voltage of the BESS. The other way of interpreting an alarm in the Hotelling's  $T^2$  control chart is to project  
 393 the observations on the space of the PCs; e.g: November (11/2017) projections chart has been superimposed  
 394 with the month of training (October/2017) as shown in Figure 9.



395  
 396 Figure 9. Projections of November observations on the space of the PCs.  
 397

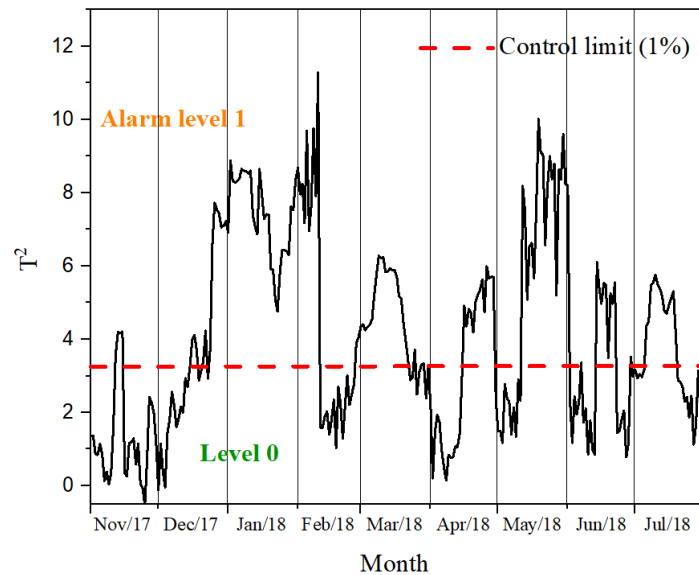
398 In this month the centroid of the observations moves in the direction of the parameter  $K_{c10c}$ , specifically on  
 399 days 12-15 November, which were marked as alarm by the  $T^2$  control chart (Figure 7), and coincides with the

400 diagnosis obtained in the contributions plots to  $T^2$  (Figure 8). However, the alarms presented during these  
401 days they are associated with an increase in the  $K_{c10}$  parameter due to a SOC below 85% which caused the  
402 controller to apply a boost charge.

403

### 404 5.3. Application to real data observation

405 At this point, the PCA model is used to monitor the SOH of the system during a longer observation period,  
406 from November 2017 to July 2018. Figure 10 shows the diagnosis of the Hotelling's  $T^2$  for the new  
407 observations set.



408

409 Figure 10. Hotelling's  $T^2$  monitoring from November 2017 to July 2018.

410

411

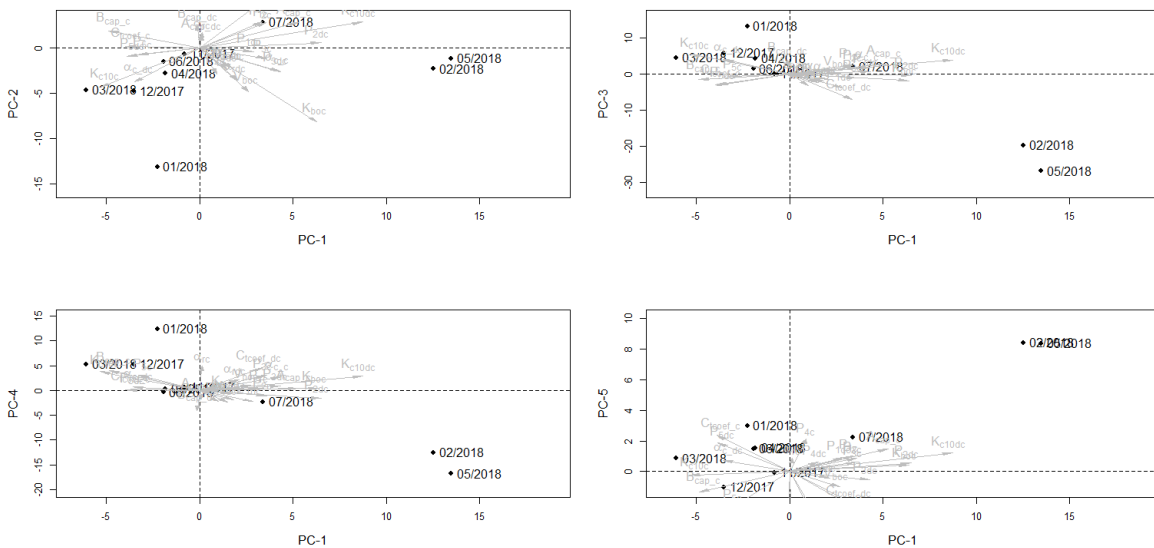
412

413 Figure 10 shows that on the third week of the month of December, an alarm signal was generated because the  
414 BESS had a SOC of less than 80%, which caused an increase of the parameter  $K_{c10}$  in the charge mode. The  
415 increase of this parameter shows that the BESS is entering a process of loss of capacity. The controller takes a  
416 week to change boost charge to float charge. However, it does not manage to lower the alarm level.  
417 According to shown in Figure 6, the following actions should have been applied: a boost charge until the  
418 battery reaches 85% and 90% of its current capacity (time for boost charge of battery = 2 h). Then perform a  
419 full charge (full charge time = 5 h) until the SOC > 90%. The same procedure should have been applied in the  
420 month of January.

421 February is the month with the greatest statistical distance between the new data and the original model  
422 (reaching up to 11 distance units), which generates a higher alarm rate. This significant increase was due to  
423 work carried out with welding equipment inside of renewable energy laboratory that led to the BESS reaching  
424 a SOC below 70%, increase in BESS current greater than 2A, and an increase of the  $P_I$  parameter in the  
425 discharge mode. During this period, the controller applied a boost charge, then changing to float charge until  
426 the BESS to working under normal conditions. Because there was an abnormal demand, then the training  
427 conditions are extremely different to the current ones so it is not possible to conclude that there is or not a  
428 failure. So, no action is required. However, subjecting the BESS to very high discharge rates over a long  
429 period is leading to a deterioration of health of the battery.

430 In March the alarms continue at a lower level. However between days 5 and 10 there is an increase in the  $K_{c10}$   
 431 parameter in charge mode. The controller applies a boost charge for 5 days until it reaches a SOC equal to  
 432 97% and then change to float charge until the alarm level falls to level 0. During the first 15 days of April,  
 433 BESS worked under normal conditions. However, the decrease in SOC ( $< 70\%$ ) caused an increase in the  $\alpha_c$   
 434 parameter in the discharge mode.  $\alpha_c$  is a parameter that is associated to the temperature variation and battery  
 435 capacity. During this month the controller begins with a float charge, then goes to a boost charge (from 10th  
 436 to 18th) and finally performs a full charge (from 19th to 25th). Again in the month of May work was done  
 437 with welding equipment inside the renewable energy laboratory. Therefore, the same decisions must be  
 438 applied as in the month of February declaring this level of alarms false. Between the days 14th and 22nd of  
 439 the month of June there are alarms caused by the increase of  $\alpha_c$  parameter in the discharge mode. The rest of  
 440 the days BESS works under normal conditions. The controller applies float charge (from 1 to 13 days), then  
 441 boost charge (14 to 22 days) and ends with float charge. However, due to the depth of discharge uncontrolled  
 442 to which the BESS was submitted during the month of May, an equalization charge should have been applied.

443 Finally in the month of July alarms (from 6 to 19 days) were by the increase of  $P_2$  parameter in charge mode.  
 444 During this month there was a greater increase in the BESS current ( $I_{bat} > 15$  A). The controller applies float  
 445 charge (from 1 to 9 days), then boost charge (10 to 19 days) and ends with an equalization charge.



446

447 Figure 11. Projections of the centroids of the observations from November 2017 to July 2018 on the space of  
 448 the PCs.  
 449

450 The unusual increase of these parameters caused a movement of the centroid of the observations (see Figure  
 451 11) and a deterioration of the BESS SOH during the first half of the year 2018 (see Figure 12). The  
 452 deterioration of health is related to a progressive loss of the BESS operational capacity. However, since the  
 453 month of May the BESS shows recovery in its SOH because the controller applied an equalization charge to  
 454 the BESS to neutralize the differences that occur in SOC of individual battery cells due to the different  
 455 behavior of the battery cells. The controller performs an equalization charge when the sum of all discharges  
 456 since the last equalization charge is 30 times the nominal capacity of the battery [43].  
 457

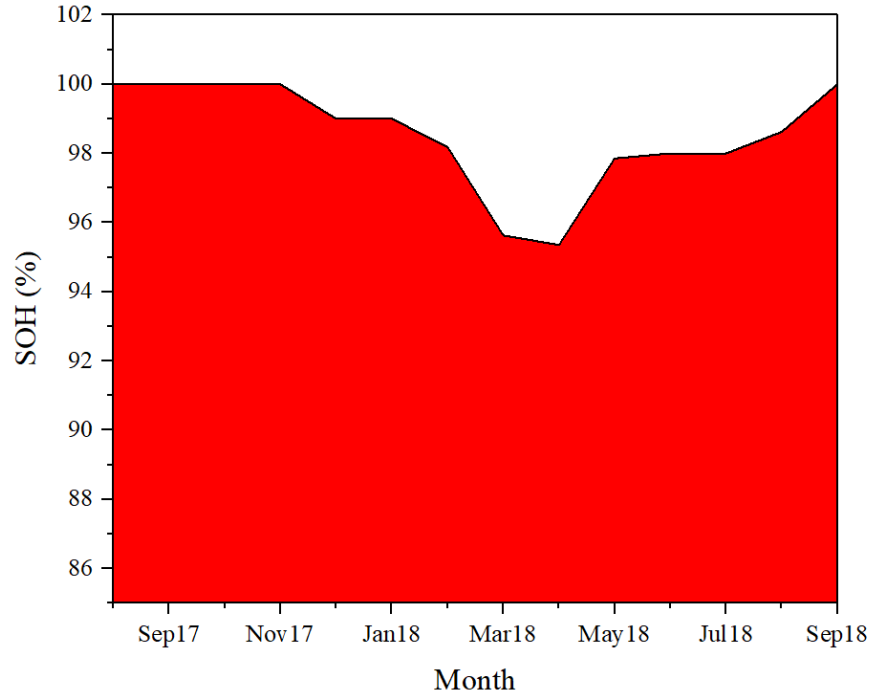
458 The SOH is estimated by Eq. (19)

$$SOH = \frac{C_{current\ max}}{C_N} \times 100\% \quad (19)$$



459

460 Where,  $C_{\text{current max}}$  is current maximum battery capacity. At the time of manufacture is considered  $SOH =$   
461  $100\%$ , and is considered  $SOH = 0\%$  when the battery capacity to store and supply energy decreases below  
462 predefined threshold [44].



463

464 Figure 12. BESS state of health (SOH) estimation of the renewable energy laboratory at Chocó – Colombia.

465

466

467

468

469

## 6. Conclusions

470

471 PCA is a versatile method capable of providing a general diagnosis of the BESS. The diagnosis is based on  
472 the study of a parameter characterizing the battery. These parameters can be identified from experimental data  
473 collected each day with an evolutionary algorithm developed in previous research. Daily, the new parameters  
474 are projected over the PCA model, which was trained on a normal working month. The analysis reveals that  
475 in the last semester of the period under study, the BESS presented alarms associated with deterioration in  
476 SOH as a result of the different operating modes of the controller. The effect over PCA projections is a  
477 movement of the observations centroid with respect to the training period. The goal of the controller is the  
478 recovery of the SOH. However, the use of aggressive charging modes increases the current, and therefore  
479 increases the BESS temperature. The effect of these increases, if they are maintained over time, is a loss on  
battery health.

480

481 Moreover, the diagnosis proposed in this paper has found that once the alarm is generated the controller takes  
482 several days to perform the charge change. Therefore, the use of the PCA diagnosis algorithm will lead to a  
483 faster change in the operation mode to recover the battery quicker, so the BESS will suffer lower currents and  
lower temperature increases.

484 The methodology presented also allows the detection of false alarms in the BESS, such as those registered in  
485 the months of February and May. Therefore, no corrective should be taken if the algorithm rises a false alarm  
486 diagnosis.

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492  
493 **Author Contributions:** All authors have worked on this manuscript together and all authors have read and  
494 approved the manuscript.

495

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