

# REMOTE MEASUREMENTS OF ELECTRICAL QUANTITIES: A STRATEGY FOR REAL TIME MONITORING OF STATIONARY BATTERIES

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**Abstract** – The paper discusses the remote real time monitoring of stationary batteries operating in real condition as a strategy to reduce maintenance costs while improving their efficiency and lifecycle. Measurements of electrical quantities remotely performed through a proposed strict protocol were compared with data provided by conventional devices. Within a confidence levels of 95% and 99%, statistical analysis confirmed that the remote system build up credibility and improves the real time monitoring system.

**Keywords:** metrology, remote real time monitoring measurement, electrical voltage, stationary batteries, backup system.

## 1. INTRODUCTION

The generation, transmission and distribution of electricity are extremely important in today's world for all activities in the industry. These systems are not perfect and therefore subject to operating problems. However, several large applications (eg: data center, call centers, power substations, control subway traffic) require a high degree of reliability and cannot fail to operate if there is a breakdown in their commercial energy system. In cases of failures, a source backup power system is usually used to overcome the lack of energy during this period of failure, which can last for minutes or even hours [1]. Therefore, the electric accumulator, also called battery, is the most commonly used energy source under this adverse operating condition. This is one of the few devices that can store energy for long periods of time and make it available on request.

In a power substation, the battery usage is of vital importance to ensure reliability of ancillary services. It is the battery that ensures that all the command and control of electronic components remain in operation during a commercial power failure. The lack of battery performance can cause significant losses in a power substation causing even disrupting of the energy supply [2].

Different studies [3-5] have shown that lead-acid batteries (most commonly used battery technology in backup application systems) degrade due to the variation of its internal resistance, a disgrace that severely impacts on the battery lifetime. It was based on this finding that the battery internal resistance is now considered critical property to

assess, in a robust and reliable fashion, the degree of degradation of the stationary lead-acid batteries.

In order to optimize the operation and maintenance costs and circumvent the shortage of skilled labor, companies are investing in automated solutions to remote monitoring their equipment [6].

## 2. SYSTEM FOR REAL TIME MONITORING

Figure 1 illustrates the proposed prototype showing the architecture of the remote monitoring system, the measurement unit (UM) and the control unit (UC) for each group of sixty-four batteries installed in a substation chosen to test the overall system performance. For each battery maintained in a controlled environment (ambient temperature and relative humidity monitored) measurements of electrical voltage, electrolyte level, impedance interconnect resistance and ripple current were carried out. These measurements were remotely transmitted via wireless communication for control units that stores and processes the arriving data and transmits them via GSM network to a server. The data is processed and analyzed by the battery management software (SIMBA-GEBAT). The system monitors the battery for its use in load, also indicating failures or breakdowns in power supply. The prototype measures the resistance value (ohm) through the impedance technique, which uses alternating current and voltage at a pre-established known frequency.

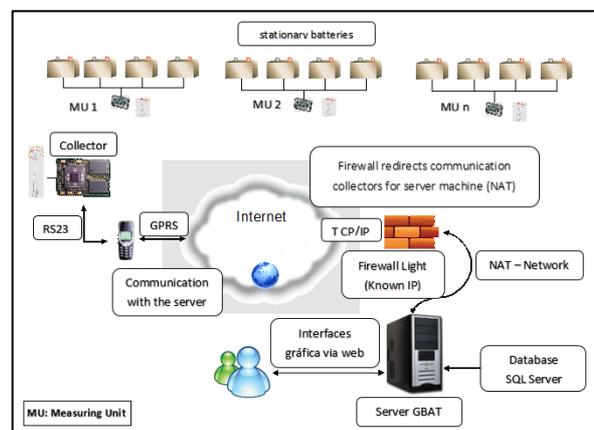


Fig. 1. Architecture of the remote monitoring system

### 3. EXPERIMENTAL PROCEDURE

Even though the remote real time measurement system processes the above-mentioned electrical quantities, this paper focuses on measurements of the electrical voltage across the battery terminals. Individual measurements performed by the automated remote system (Simba-Gebat) and by the calibrated portable measuring. A statistical analysis (parametric and non-parametric hypothesis tests) was developed for three levels of confidence (95 and 99%) allowing the validation of the real time remote system.

The portable device used was the CE 2000 model, manufactured by the World Energy Labs that uses a 4-wire measurement methodology to perform internal measurements of the battery resistance.

Measurements of electrical voltage were performed at regular intervals (weekly), along a two-month time interval. The electrical voltage was systematically measured for each one of the sixty battery (battery group) of the remote unit tested. Each measurement was repeated 6 times, totalizing 360 measurements in the two-month period. In compliance with manufacturer's recommendations, measurements were always performed keeping the battery in the floating condition.

### 4. STATISTICAL ANALYSIS

The two data sets shown in the Annex comprise the data samples considered in the statistical analysis:

- **Sample s1** (laboratory measurements): electrical voltage measurements obtained in real operating conditions (Simba-Gebat measurements);
- **Sample s2** (field measurements): electrical voltage measurements obtained given by the calibrated portable device.

#### 4.1. Descriptive statistics

Table 1 summarizes the statistical analysis performed for both: measurement results of the Simba-Gebat remote system and of the portable device.

Table 1. Descriptive statistics of experimental data

Statistical parameter	Simba-Gebat	Portable Device
average	2.20V	2.19V
median	2.19V	2.19V
mode	2.22V	2.19V
standard deviation	0.0109V	0.01V
sample variance	0.00012V <sup>2</sup>	0.0001V <sup>2</sup>
kurtosis	-0.816	4.42
asymmetry	0.093	-0.91
sample size	360	360

Table 2 shows the absolute frequency distribution ( $F_i$ ) for the Simba-Gebat and Portable Device electrical voltage measurements.

Table 2. Absolute frequency distribution of experimental data

Electrical Voltage (V)	Simba-Gebat: Absolute Frequency ( $F_i$ )	Portable Device: Absolute Frequency ( $F_i$ )
2.17	24	25
2.19	32	314
2.20	99	17
2.22	118	1
2.23	87	3

Figures 2 and 3 illustrate, respectively, histograms of electrical voltage measurements performed, respectively, by the Simba-Gebat remote system and by the calibrated portable device.

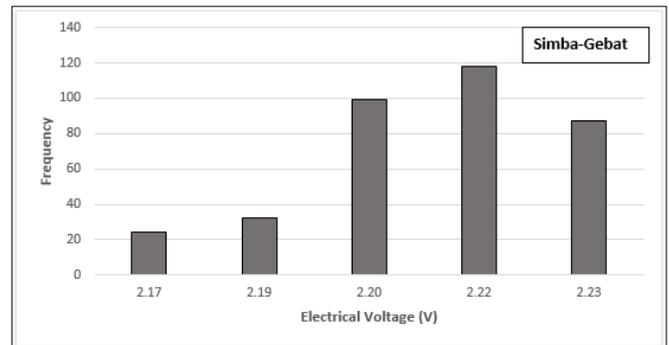


Fig. 2. Histogram: voltage measurements of Simba-Gebat

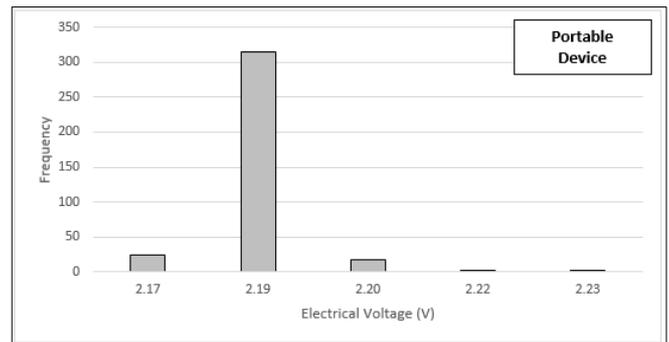


Fig. 3. Histogram: voltage measurements by the portable device

For both samples, results of the statistic analysis confirmed that mean, median and mode values are alike, inferring that the populations of these samples follow a normal probability distribution. Even though this behaviour may suggest a normal distribution it does not confirm the Gaussian profile hypothesis.

#### 4.2. Normality test: Kolmogorov-Smirnov (K-S)

This normality test states that:

- **Null Hypothesis (H<sub>0</sub>):** the sample data follow a Gaussian distribution
- **Alternative Hypothesis (H<sub>1</sub>):** the sample data do not follow a Gaussian distribution

In order to confirm that the Simba-Gebat experimental data indeed follow a normal distribution, the K-S test (at confidence levels of 95% and 99%) was applied.

The acceptance criterion for the Null Hypothesis (that automatically rejects the Alternative Hypothesis) is  $D_{max} \leq D_{crit}$ , where  $D_{max}$  denotes the test statistic and  $D_{crit}$  a critical value extracted from the Dixon distribution for a given confidence level (in this work, two confidence levels were considered: 95% and 99%).

Equation (1) allows calculation of the  $D_{max}$  value:

$$D_{max} = \frac{d_n}{N} = \frac{|F_{a_n} - e_{a_n}|}{N} \quad (1)$$

where the subscript  $n$  denotes the interval number;  $F_{a_n}$  the cumulative absolute frequency given by equation (2);  $e_{a_n}$  the cumulative nominal frequency given by equation (3) and  $N$  the sample size. In Equation (1):

$$F_{a_n} = F_{a_{n-1}} + F_{i_n} \quad (2)$$

$$e_{a_n} = e_{a_{n-1}} + e_{i_n} \quad (3)$$

where:

$F_{i_n}$  denotes the absolute frequency of the experimental data and  $e_{i_n}$  the theoretical frequency of the experimental data.

The theoretical frequency ( $e_{i_n}$ ) is given by:

$$e_{i_n} = [F(Z_{2n}) - F(Z_{1n})] \cdot F_{i_n} \quad (4)$$

In this expression,  $F(Z)$  is associated with the area of the normal (theoretical) distribution; i.e.:  $F(Z_2)$  and  $F(Z_1)$  refer, respectively, to the areas underneath the assumed normal distribution curve limited by the  $Z_2$  and  $Z_1$  abscise values, calculated by equations (5) and (6):

$$Z_{1n} = \frac{x_{1n} - \mu}{\sigma} \quad (5)$$

$$Z_{2n} = \frac{x_{2n} - \mu}{\sigma} \quad (6)$$

In these expressions:

$x_{1n}$  and  $x_{2n}$  denote, respectively, the lower and upper limits of the electrical voltage of the experimental data (V);

$\mu$  (V) is the mean value of the experimental data (population);

$\sigma$  (V) is the standard deviation of the population.

Tables 3 and 4 illustrate, respectively, the results of the calculated cumulative absolute frequency ( $F_a$ ) and the cumulative theoretical frequency ( $e_a$ ). Table 5 shows results of the calculation of the test statistic ( $D_{max}$ ) applicable to the results of electrical voltage measurements (V) of the tested batteries.

Table 3. Cumulative absolute frequency

Interval Number	Electrical Voltage	Electrical Voltage	Absolute Frequency	Cumulative Absolute Frequency
	$x_1$	$x_2$	$F_i$	$F_a$
	(V)	(V)	-	-
1	[2.17	2.19]	56	56
2	(2.19	2.20]	99	155
3	(2.20	2.22]	118	273
4	(2.22	2.23]	87	360

Table 4. Cumulative theoretical frequency

Interval Number	Electrical Voltage	Electrical Voltage	Parameter Z: Normal Distribution		Area of interval in the Normal Distribution		Theoretical Frequency	Cumulative Theoretical Frequency
	$x_1$	$x_2$	$Z_1$	$Z_2$	$F(Z_1)$	$F(Z_2)$	$e_i$	$e_a$
	(V)	(V)	-	-	(%)	(%)	-	-
1	[2.17	2.19]	-2.48	-0.55	1.86	34.29	18.2	18.2
2	(2.19	2.20]	-0.55	0.09	34.29	39.73	25.7	43.9
3	(2.20	2.22]	0.09	1.38	39.73	15.48	52.9	96.7
4	(2.22	2.23]	1.38	2.75	15.48	99.10	72.7	169.5

Table 5. Test statistic ( $D_{max}$ )

Interval Number	Theoretical Frequency	Cumulative Theoretical Frequency	Absolute Frequency	Cumulative Absolute Frequency	$ F_a - e_a $	Test Statistic
	$e_i$	$e_a$	$F_i$	$F_a$	$d$	$D$
1	18.2	18.2	56	56	37.8	0.105
2	25.7	43.9	99	155	111.1	0.309
3	52.9	96.7	118	273	176.3	0.490
4	72.7	169.5	87	360	190.5	<b>0.529</b>

The results shown in Table 5 confirm that the major difference (i.e.: the test statistic  $D_{max}$ ) is expressed by the value 0.529. The  $D_{max}$  values of Dixon Table exhibiting a size range of 4 are: 0.624 ( $\alpha = 0.05$ ); 0.733 ( $\alpha = 0.01$ ). Whereas the  $D_{max}$  value calculated is less than the  $D_{crit}$  values tabulated, the null hypothesis ( $H_0$ ) was accepted for each significance level ( $\alpha$ ) assessed. Therefore, one concludes that the sample data follow normal distribution for a confidence level  $(1-\alpha)$  of 95% and 99%.

Similarly, it is concluded that the sample data  $s_2$  follow a Gaussian distribution. In this case, the test statistic ( $D_{max}$ ) results in the value 0.613. Since this is an estimate which leads to a value less than the  $D_{max}$  values of Dixon table with a size range of 4, it can be said that the sample data  $s_2$  follow a normal probability distribution for confidence levels of 95% and 99%.

#### 4.3. Variance test

To verify that the population variances of the two samples studied are statistically equal, one applies the Test-F. Although the null hypothesis ensure that two samples of the population variances are equal, the alternate hypothesis supports the assumption that they are different, as shown below:

$$H_0: \sigma_a^2 = \sigma_b^2$$

$$H_1: \sigma_a^2 \neq \sigma_b^2$$

Applying (7) was calculated the statistic of Test-F:

$$F = \frac{S_a^2}{S_b^2} \quad (7)$$

In this expression:

$S_a$ : standard deviation (sample a)

$S_b$ : standard deviation (sample b)

When calculated, the statistics of the Test-F leads to the value  $F = 1.20$ .

Figure 5 illustrates the acceptance of region (RA), and the rejection of region (RC) associated with null hypothesis with the critical values of Table F for confidence levels of 95% and 99%, respectively. It can be observed that the null hypothesis ( $H_0$ ) is accepted for the two confidence levels studied. Thus, the population variances, even if unknown, can be considered statistically equal in light of the confidence levels for the statistical condition in which the hypothesis  $H_0$  was accepted.

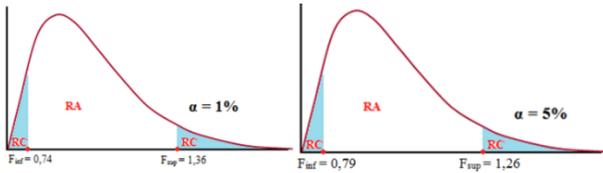


Fig. 4. Test-F: evaluation of the null hypothesis

#### 4.4. Independence

The measurements performed by SIMBA-GEBAT and by the portable device were considered independent because the measurement value given by the remote system proved not to affect measurement results given by the instrument and vice versa. Moreover, the batteries are considered independent and the electrical voltage values of an element proved not to affect the value of the same magnitude measured in another battery.

#### 4.5. Difference test between two means

The null hypothesis ensures that both samples of the the population have the same mean value; even though the alternative hypothesis shows that they are different, as shown below:

$$H_0: \mu_a = \mu_b$$

$$H_1: \mu_a \neq \mu_b$$

Equation (8) shows the expression for calculating the statistic test-t:

$$t = \frac{(\bar{x}_a - \bar{x}_b) - d}{S_c \cdot \sqrt{\frac{n_a + n_b}{n_a \cdot n_b}}} \quad (8)$$

In this expression:

$\bar{x}_a$ : sample a mean;  $\bar{x}_b$ : sample b mean

$d$ : difference between population a and b mean;

$S_c$ : common standard deviation

$n_a$ : sample  $s1$  size;  $n_b$ : sample  $s2$  size

The common standard deviation ( $S_c$ ) is calculated applying (9):

$$S_c = \sqrt{\frac{(n_a - 1) \cdot S_a^2 + (n_b - 1) \cdot S_b^2}{n_a + n_b - 2}} \quad (9)$$

From Equation (8) it becomes possible to calculate the statistical test-t:

$$t = 0.95$$

Figure 5 illustrate the acceptance region (RA), and the rejection region (CR), associated with the null hypothesis of the Table *Student t test* for confidence levels of 95% and 99%, respectively. It can be observed that the null hypothesis ( $H_0$ ) is accepted for the two confidence levels studied. It follows, therefore, that the electrical voltage measurements performed by the SIMBA-GEBAT are statistically equal to those performed by the calibrated portable device for confidence levels of 95% and 99%.

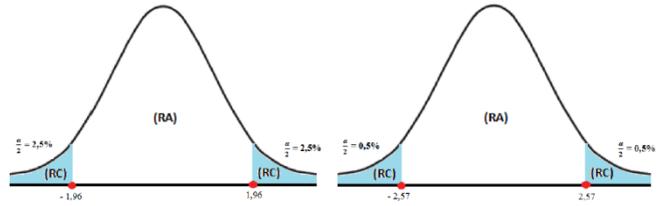


Fig. 5. Test-t: evaluation of the null hypothesis

## 5. CONCLUSIONS

Real time operating conditions (ie: in the field) proved to be an attractive remote monitoring technique for assessing the performance of stationary batteries in the laboratory environment.

The statistical validation of the SIMBA-GEBAT measuring system was performed through the *t-Student test*. The significance test for equality between two mean showed that the electrical voltage measurements performed by the Simba-Gebat system and the portable device may be considered statistically equal for confidence levels of 95% and 99%.

The validated system proposed in this study introduces the beneficial advantages of (i) reducing operational maintenance costs enabling the utility to perform automatic real time measurements without the interference of experienced personnel that are vulnerable to human errors.

This alternative proposed methodology, validated and tested within real operating condition in a power substation, is ready to be introduced to the market and available to other dealers interested in use it, therefore participating of this national technological innovation initiative.

## REFERENCES

- [1] G. Rangel, MSc Dissertation, Remote measurement as strategy to monitor stationary batteries: case study in an electric power substation (in Portuguese), Postgraduate Programme in Metrology (PósMQI), Rio de Janeiro, RJ, BRAZIL, 2012.
- [2] J. Hernandez, G. Pesenti and M. Frota, “Metrological evaluation of a stationary remote monitoring battery system” (in Portuguese), *III International Congress in Mechanical Metrology*, pp. 1-6, Gramado, RS, Brazil, 2014.
- [3] G. R. Pesenti, Rosolem, R. F. Beck, M. G. R. L. A. Soares, G. R. Santos, P. H. Lopes, R. S. Nazari, V. T. Arioli “Remote monitoring system for stationary lead-acid batteries” (in Portuguese), SENDI, Rio de Janeiro. 2012.
- [4] G. R. Pesenti, Rosolem, R. F. Beck, M. G. R. L. A. Soares, G. R. Santos, V. T. Arioli, P. T. Frare, P. H. Lopes “Stationary lead-Acid batteries maintenance management system”, INTELEC, Orlando, USA, 2010.
- [5] M. F. Rosolem, R. F. Beck, P. E. Cardoso, L. A. Soares, F. Yamaguti “Stationary VRLA battery evaluations: Internal measurements and capacity test. An experience at the Claro Cellular Mobile Company”, Battcon, Florida, USA, 2004.
- [6] G. R. Pesenti, Rosolem, R. F. Beck, M. G. R. L. A. Soares, G. R. Santos, V. T. Arioli, P. T. Frare P. H. Lopes “The batterie’s regulatory process in Brazilian Telecommunications Industry”, Telescon, Viena, Austria, 2009.