Soft sensors to assess the energy consumption in the formation of lead-acid batteries

CABELLO, J.J.[a], SAGASTUME, A.[a], SOUSA, V.[a] HERRERA, H.[a], BALBIS, M.[a], SILVA, J.[a]

a. Universidad de la Costa. Colombia.

Abstract

Lead-acid batteries are essential for different economic activities and are, in general, energy intensive products. However, there is a limited discussion on how to assess the energy consumption and its efficiency for battery manufacturing. This study assess the process of battery formation, which is essential in manufacturing lead-acid batteries, and account for over half of the energy consumption of battery production. The assessment is implemented in a battery plant using data from a 4 years period to develop an energy performance indicator (EnPI), used to assess the efficiency of battery formation. To implement the EnPI a soft sensor is developed. Results show that the implementation of the proposed EnPI combined with other measures, resulted in a reduction of 3 to 5% of the electricity consumption of battery formation.

Keywords: *Battery formation, energy efficiency, battery production*

1. Introduction

Cleaner Production (CP), defined by the United Nations Industrial Development Organization (UNIDO: https://www.unido.org/cp/o5153.html) as a preventive, integrated strategy, is applied to production systems to (Cabello et al., 2013):

a) Increase productivity by ensuring a more efficient use of raw materials, energy and water;
b) Promote better environmental performance through reduction at source of waste and emissions;
c) Reduce the environmental impact of products through their life cycle by the design of environmentally friendly but cost-effective products.

Therefore, CP aims, among others, to an improved energy efficiency (EE) of productive systems. Moreover, EE assessments can be used as a first step to motive companies to introduce the CP approach.

Energy consumption is at the center of a global debate because of its implications on global warming and climate change (among other environmental impacts) and on the global economy. This generate a demand for novel energy monitoring and management methods capable to forecast energy consumption to support the process of decision making in the distribution and accounting of energy within production systems (Weinert et al., 2011). Furthermore, a lack of adequate methods to effectively address EE, and support energy monitoring and management, in different industries has been evidenced (Bunse et al., 2011), which stresses the need for more comprehensive EE assessments (Giacone and Mancò 2012).

Lead-acid batteries, which accounted for a 41.5 billion USD market value in 2010 (Miloloža, 2013), are classified in: Lighting, Starting and Ignition (LSI) batteries (mainly used in the automotive sector), traction batteries (for electrical vehicles) and stationary batteries. The production of lead-acid batteries implies the use of 15 to 36 MJ per kg of finished battery (depending if the battery is made from virgin or recycled materials), of which 5.8 to 9.6 $MJ/kg_{battery}$ are used in battery manufacturing (Rantik, 1999; Dahodwalla et al., 2000; Rydh and Sandén, 2005; Sullivan and Gaines, 2010; Sullivan and Gaines, 2012). In total, battery manufacturing account for 30% of the overall energy consumption. However, regardless of been an energy intensive product (Pavlov 2011; Report Buyer 2015; Rydh 1999; Sullivan and Gaines 2012), to the best knowledge of the authors, there are no studies in specialized literature addressing the EE and management of lead-acid battery manufacturing.

Lead-acid battery manufacturing entails three main steps, namely: Grid manufacturing, battery assembly and the battery formation process. In particular, the formation process accounts for over 50% of the overall manufacturing energy consumption (Jung et al., 2016). In this process the battery is charged for the first time, while the lead alloy plates are transformed into positive and negative electrodes through different chemical reactions. This process significantly influences the battery lifespan and performance as well as its production costs (Cope et al., 1999; Thi Minh, 1999; Pavlov et al., 2000; Petkova and Pavlov, 2003). Hence, improving the EE of battery formation is essential towards and improved EE of battery manufacturing and must be carefully controlled (Kiessling, 1992).

Given the importance of battery formation on the energy consumption, costs and quality of battery manufacturing, this study aims at developing an energy efficiency assessment of the battery formation process.

2. Battery formation

The development of the battery formation process defines the lifespan and the overall performance of batteries (Cope et al. 1999; Thi Minh 1999; Pavlov et al. 2000; Petkova and Pavlov 2003). Different algorithms have been developed to control the electric current and voltage during battery formation, of which the intermittent charge regime (ICR) is the most used (Pavlov et al. 2000; Wong et al. 2008). This algorithm includes two operation modes: constant current (CC) and intermittent current (IC). Five control parameters, three voltage levels (V_{INI}, V_{IC1}, V_{IC2}) and two current levels (I_{IC1}, I_{IC2}), are used to control this algorithm (see).

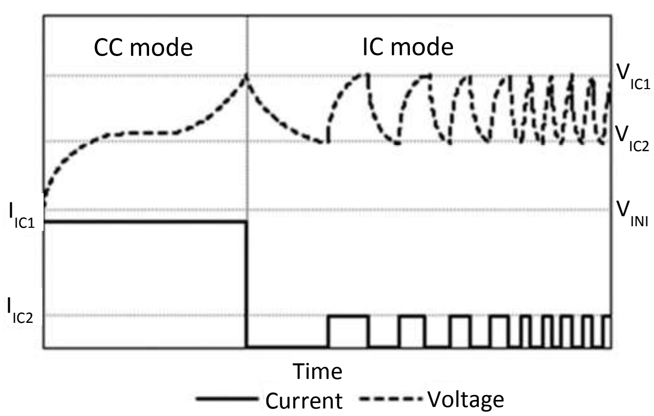

Fig. 1. Intermittent charge regime algorithm of battery formation.

In CC mode, the battery is charged with a constant current (I_{IC1}) to over 97% of its state of charge (SOC), while voltage increases from V_{INI} to V_{IC1}. Once the circuit reach the upper control voltage (V_{IC1}) the CC mode stops and the IC mode initiates. In IC mode the battery is charged up to 100% of its SOC, in this case current varies between I_{IC2} and 0, while voltage varies between V_{IC1} and V_{IC2}. An overcharge of 2 to 3% is applied to equalize cell voltages (Wong et al. 2008).

To implement the control algorithms, the formation process includes sensors (to for the real-time measure of the voltage, current, ampere-hours accumulated in batteries and the electrolyte temperature within the battery) and a data acquisition module to store measurements in a database. Each battery model has a specific formation algorithm, been the main control parameter the electric charge (i.e. the ampere-hour to be supplied to the battery), which is used to finish the process (once the battery receive the demanded electric charge the formation stops) (Chen et al., 1996).

The formation circuit includes an AC/DC rectifier and a batch of batteries connected in series (see Fig. 2), thus two subcircuits can be identified: the AC/DC rectifier and the batch of n batteries.

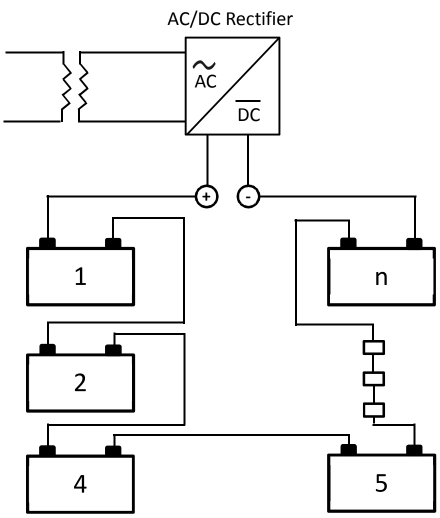

Fig. 2. Formation circuit.

The overall electricity consumption of battery formation depends on the number of batteries been simultaneously formed in the circuit, the voltage used in the process and the electric charge of the battery model. The electricity consumed in the formation of a batch of batteries can be calculated as (Kiessling, 1992):

$$E_B = N \cdot V_{DC} \cdot C \quad (1)$$

Where: E_B is the electricity consumed in the formation of a batch of batteries, N is the number of batteries in the batch, V_{DC} is the voltage used in battery formation and C is the electric charge of the battery model. Moreover, the overall electricity supplied to a formation circuit (E_T) accounts for the sum of the energy used in battery formation (E_{BF}), the energy loss within the batteries (E_{LB}, because of the exothermal chemical reactions that causes heat loss and the emissions of H and O_2), the energy loss in the batch of batteries subcircuit (E_{LC}) and the energy loss in the AC/DC rectifier (E_{LR}):

$$E_T = E_{BF} + E_{LC} + E_{LB} + E_{LR} \quad (2)$$

Most of E_T is used in the formation circuit. The electricity supplied to the battery batch subcircuit (E_{BB}) is:

$$E_{BB} = E_{BF} + E_{LC} + E_{LB} \quad (3)$$

Most of E_{BB} is used in the formation process, the rest is loss within the battery and in the wires and connectors of the battery batch subcircuit. In general, the efficiency of battery formation on the technology used, its technical state, on the operational practices and on the energy quality in the AC network (Kiessling, 1992).

The efficiency of battery formation is difficult to assess in real-time, because of the difficulty to accurately measure E_B that would require the use electric meters for each formation circuit in a battery plant, which is rather costly. In this case, the use of soft sensors (SS) is recommended. SSs make real-time calculations of process parameters (that are either too difficult or too expensive to measure) based on the real-time measures of other process parameters (Kadlec et al., 2009; McAvoy, 1992). The use of SSs have been successfully implemented to different energy systems (Alabbasi, 2014; Hadid et al., 2014; Järvisalo, 2016; Zeng and Wang, 2010; Zhanpei et al., 2014).

The electricity consumed in the formation of a batch of batteries can be calculated from the measures of the current and voltage measured to control the formation algorithm (Ponce and Moreno, 2015):

$$E_{BB} = \int_0^t p(t) \cdot dt = \int_0^t V_{DC}(t) \cdot I_{DC}(t) \cdot dt \quad (4)$$

Where: p is the power supply, V_{DC} the voltage and I_{DC} the current in the power supply.

Given the difficulties to analytically solve equation 4, a numerical method (i.e. the trapezoidal rule) is used.

$$E_{BB} = \sum_{i=1}^{n} V_{DCi} \cdot I_{DCi} \cdot t \qquad (5)$$

Where: n is the number of data used, V_{DCi} voltage in the i^{th} interval, I_{DCi} current in the i^{th} interval and t time between intervals, which is calculated as:

$$t = \frac{T}{n} \qquad (6)$$

Where T is the time of the formation of a batch of batteries.

Based on E_B is possible to introduce and energy performance indicator (EnPI) to assess the EE of battery formation. Hence, the database can be integrated to define an energy baseline (EnBL) as recommended by ISO 50001 (ISO, 2011). An EnPI would allow to rapidly introduce corrective actions, which is very important towards higher EE standards (Cabello et al., 2016).

3. Soft sensors

Monitoring process parameters with sensors and instrumentation is essential to control industrial processes towards optimum and save operations. However, there are some parameters too difficult or too costly to assess. In this case the development of SSs, based on available measures of other parameters to be used in either statistical models or with natural laws and principles, to estimate the value of the difficult parameters are indicated (Chowdhury, 2015; Kadlec et al., 2008; Kaneko and Funatsu, 2016; Liu, 2016; Mansano et al., 2014). There are different applications of SSs in energy management and assessments: in buildings (Velázquez et al., 2013; Thanayankizil et al., 2013; Li et al., 2014; Ploennigs et al., 2011), in industry (Hadid et al., 2014; Qi et al., 2015; Zhao et al., 2015; Kortela and Jämsä-Jounela, 2012; Zhang et al., 2008; Leonow and Mönnigmann, 2014; Järvisalo et al., 2016).

There are different approaches to develop a SS (Fortuna et al., 2005; Gomnam and Jazayeri-rad, 2013; Hong et al., 1999; Kalos et al., 2003; Chowdhury et al., 2015; Warne et al., 2004). In particular Kadlec et al. (2006) proposed a forth steps general methodology:

1. Data inspection: focused on an overview of the available data, its structure, availability, trends, and accuracy. In addition, a target parameter is defined as well as the mathematical model to be used (i.e. simple regression model, more complex regression models, neural network, etc.).

2. Selection of representative data as a reference for the SS model.

3. Model selection: Since there no generalized method, usually the model and its parameters are specifically selected for each SS (Friedman et al., 2001).

4. SS validation. There are different ways to validate a SS. In general, statistical methods like the Mean Squared Error, which quantifies the mean square distance between the estimated and the measured parameter, are used (Fortuna et al., 2007).

4. Case study

A battery plant in Colombia is selected for this study. Battery production in this plant steadily increased at an average 14% in the last years, with the electricity consumption showing a similar growing trend. Therefore, improving the electricity efficiency is essential for the plant economy. In total battery formation consumed an average 480 MWh per month, accounting for 53% of the overall electricity consumption of the plant. The battery formation section includes 17 tables with 12 circuits per table. Formation circuits in this section are design for a batch of 18 batteries.

4.1 EE of battery formation.

To assess the EE, an energy performance indicator (EnPI) is developed. Since there are significant differences between the battery models manufactured in the plant (i.e. different sizes and capacities), the concept of equivalent production, suggested by ISO (2014), is used to introduce the equivalent battery (Q_B):

$$Q_B = P \cdot k_b \qquad (7)$$

Where P stand for the produced batteries and k_b is the battery electric charge coefficient, which is calculated as:

$$k_{b-j} = \frac{C_{b-j}}{C_{bmin}} \qquad (8)$$

Where C_{b-j} is the electric charge of the j^{th} battery model and C_{bmin} is the electric charge of the smaller battery model.

There is currently no way to measure the electricity loss in the AC/DC rectifier. Moreover, to control the formation algorithm direct measures of the current and voltage input to the battery batch subcircuit are made. These measures can be used to calculate E_{BB}. Therefore, the proposed EnPI is a relation between electricity supplied to the battery batch subcircuit and the equivalent batteries:

$$EnPI = \frac{E_{BB}}{Q_B} \qquad (9)$$

Also, an EnBL, as recommended by ISO (2011), is developed for each circuit of the formation section.

In total, 10,286 formation batches (18 batteries each for over 200 models) were developed between July 2014 and July 2015. A random sample of 2,902 batches, for 98% confidence interval, is used in the study. The EnPI is individually calculated for each circuit. shows the correlation between E_{BB} and Q_B.

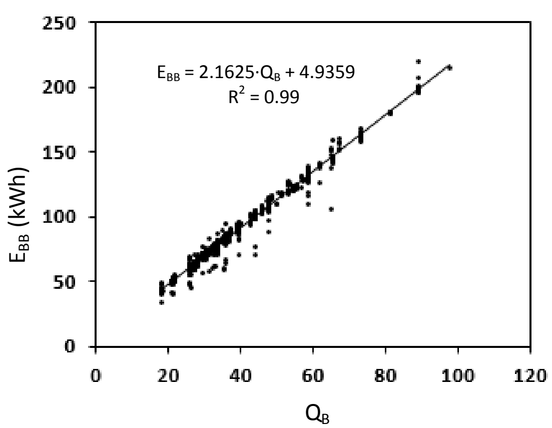

Fig. 3. Linear regression analysis: E_{BB} vs.

The linear regression results in a high correlation (R^2 = 0.99), which proves the usefulness of both the EnPI and the EnB.

4.2 Soft sensor development.

There are 204 formation circuits in the formation section. Installing sensors for the real-time monitoring of the electricity consumption in each circuit is both expensive and complicated. However, the real-time monitoring of process parameters to control the formation algorithm, including the current and voltage needed to calculate the electricity consumption are used in a SS for the real-time calculation of the electricity consumed and the EnPI of battery formation. The SS is developed following the methodology depicted in section 3 and using the data assessed in section 4.1. For the mathematical model equation 5 is used.

The sensor is validated with the approach proposed by Qui et al. (2015). An energy quality analyzer is used to directly measure E_{BB} in the formation of 170 batches for 5 different battery models in 17 circuits. For these batches, E_{BB} is also calculated with the SS. Results are compared in a scatter plot.

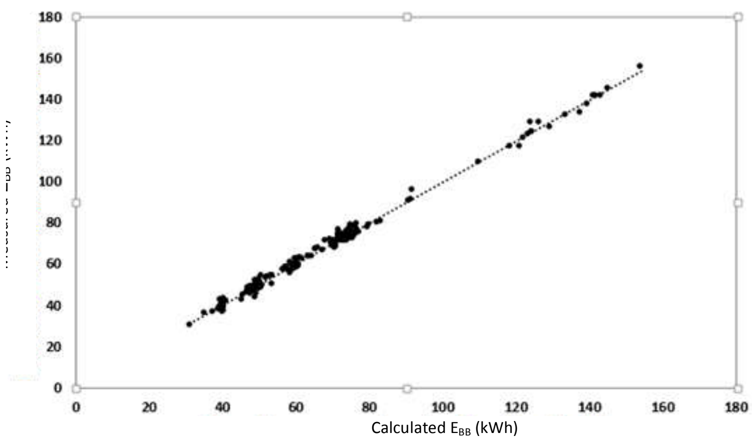

Fig. 4. Scatter plot: Measured E_{BB} vs. Calculated (with SS) E_{BB}.

From Fig. 4 the SS has a mean error of 0.4 kWh (0.52% of the mean electricity consumption), with a standard deviation of 0.62 kWh. These results validate the accuracy of the SS to measure the electricity consumption based on the parameters currently measured during battery formation.

5. Results and discussion

The SS was implemented in battery formation between January and July 2016, allowing to assess the energetic performance, for the formation of each batch of batteries, with the EnPI. Moreover, the EnPI allows to assess the trends of the energetic performance at different levels:

- ✓ <u>Formation circuit level</u>: allows to quickly identify the loss of efficiency and the malfunctioning of sensors on the formation circuits. Hence, corrective measures can be rapidly implemented.
- ✓ <u>Operation staff level</u>: the EnPI is measured for the formation process operated by each operative staff team. Thus the efficiency trends associated with this staff can be closely monitored, rapidly identifying malpractices.
- ✓ <u>Management level</u>: the trend of the average EnPI of the formation section is monthly assessed for the plant managers, where the stakeholders decide which actions/investments are needed when negative trends are detected in the energetic performance.

The systematic control of the EnPI at the different levels allowed to identify electricity saving opportunities related whit the technical condition of the formation circuits and the adequate actions to improve the efficiency:

1. Develop a protocol to certify the technical condition of the wires and connectors used in the formation circuit.
2. Clean the surface of connectors before using them in battery formation.
3. Redesign connectors.
4. Establish regular thermographic assessments to detect heat losses on wires and connectors.
5. Improve the maintenance system of the formation circuits.

Another source of inefficiencies is detected in the voltage used in the formation process (averaging 17.6 V), which is higher than the recommended maximum of 16 V (Kiessling 1992; Prout 1993; Pavlov 2011). From equation 4, the electricity consumed is directly proportional to both, the voltage and the electric current. As the formation algorithm uses a constant current, the use of higher voltage results in higher electricity consumption. Aside from the energy loss, the surplus electricity consumed results in increased heat loss and emissions of H and O_2 (IEC 60095-1: 2000; Pavlov, 2011). Considering the characteristics of the electricity transformer of the plant, the voltage was set to 16.4 V.

Fig. 5 shows the monthly electricity consumption of the formation section between January and June of 2016.

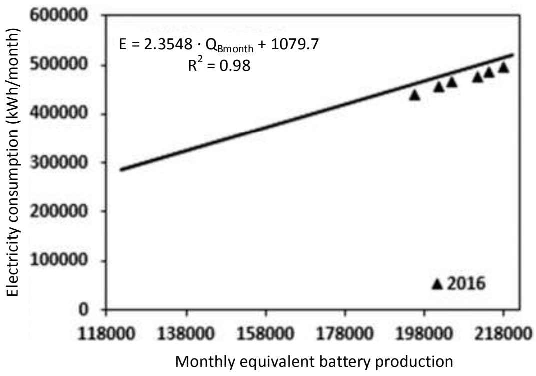

Fig. 5. Monthly electricity consumption of the battery formation section.

Results show that, although battery production increased in 2016, thus increasing the overall electricity consumption of battery formation. However, the energetic performance of the process improved from 3 to 5% as shown in Table 1. Table 1 shows the monthly electricity savings resulting the use of the SS. These savings are calculated as the difference between the electricity consumption forecasted by the EnB and the actual consumption. Savings of about 124.3 MWh (averaging 4.24 %) were achieved in the six month period of implementing the SS. In general, monthly savings are between 3 to 5%.

Table 1. Monthly and total energy saving.

Month	**Battery Production ($\cdot 10^3$)**	**Equivalent battery production ($\cdot 10^3$)**	**Electricity forecasted with EnB (MWh)**	**Actual electricity consumption (MWh)**	**Electricity Saving (MWh)**	**Electricity Saving (%)**
January	113.7	204.9	483.8	467.2	16.5	3.42
February	105.9	201.6	475.8	455.8	19.9	4.20
March	109.5	217.9	514.4	494.4	20.0	3.89
April	121.1	214.4	505.8	484.0	21.9	4.32
May	100.2	211.3	498.6	475.6	22.9	4.60
June	938.4	195.6	461.7	438.7	22.9	4.98
Total	**644.4**	**1,245.8**	**2,940.1**	**2,815.8**	**124.3**	**4.24**

6. Conclusions

Battery formation account for most of the energy consumption of battery manufacturing and its performance was successfully assessed with the use of an energy performance indicator and a soft sensor. The implementation of these tools allows to rapidly implement corrective actions towards a reduced consumption of electricity, which resulted in an average reduction of 4.4% of the electricity consumption. This impacted the production costs of batteries. Other saving opportunities exists in the AC/DC rectifier and should be subject of future investigations.

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