Energy Efficiency (2019) 12:1219–1236
https://doi.org/10.1007/s12053-018-9741-6

ORIGINAL ARTICLE

Energy management in the formation of light, starter, and ignition lead-acid batteries

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Received: 24 July 2017 / Accepted: 14 October 2018 / Published online: 26 October 2018

Abstract This paper discusses energy management in the formation process of lead-acid batteries. Battery production and electricity consumption in during battery formation in a battery plant were analyzed over a 4-year period. The main parameters affecting the energy performance of battery production were identified and different actions to improve it were proposed. Furthermore, an Energy Performance Indicator (EnPI), based on the electricity consumption of battery formation (a difficult and rather expensive parameter to measure), is introduced to assess its energy efficiency. Therefore, a Soft Sensor to measure the electricity consumption in real-time (based on the voltage and current measured during battery formation) and to calculate the EnPI is developed. Moreover, Energy Management (EM), aided by the use of energy baselines and control charts is implemented to assess the energy performance of battery formation, allowing the implementation of rapid corrective actions towards higher efficiency standards. This resulted on the average in a 4.3% reduction of the electricity consumption in battery formation.

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Keywords Energy management · LSI lead-acid battery · Soft sensor · Battery formation process

Introduction

The energy-saving potential of the industrial sector is around 974 million tons of equivalent oil (Fawkes et al. 2016), and energy management (EM) is one of the main approaches to realize it. However, in spite of the positive outcomes of EM in industry (Block et al. 2006; Gielen and Taylor 2009; Gómez et al. 2018; Palamutcu 2010; Poscha et al. 2015; Rudberg et al. 2013), there is a need for more adequate methods and tools for a more comprehensive assessment of energy efficiency (EE) (Bunse et al. 2011; Giacone and Mancò 2012). In addition, Weinert et al. (2011) and Madrigal et al. (2018) stressed the importance of developing novel energy monitoring methods, to further support decision-making towards a more efficient use of energy in production systems.

Lead-acid batteries are energy-intensive products consuming over their life cycle large quantities of electricity and fuel (Pavlov 2011; Report Buyer 2015; Rydh 1999; Sullivan and Gaines 2012). They are widely used in several applications (e.g., in vehicles). However, there is a rather limited discussion in the specialized literature approaching the energy consumption and management of lead-acid battery manufacturing. Wang et al. (2015) proposed an approach to optimize the energy costs of battery manufacturing, rather than the energy consumption, by addressing the energy price fluctuations. However, the same authors point out that this approach is rather difficult to implement, and more realistic energy consumption models and pricing mechanisms are required to improve its results. Following a similar approach, Wang et al. (2017) proposed an optimization model to minimize the costs of the electricity used in battery formation. This model focuses on the time-of-day electricity price, and on the variation of the AC/DC rectifier efficiency with the load rates (i.e., the ratio between load power and the nominal power). The energy losses in the battery subcircuit are not considered within this model. The optimization results from the model define the starting time of the formation process, moving the higher power loads to the lower time-of-day electricity price, while moving the lower power loads to the higher time-of-day electricity price. The same authors point to a potential current overload of electric systems if the model is implemented. Using a different approach, an electricity management methodology was introduced in the manufacturing of lead-acid batteries in a battery plant (Sagastume et al. 2018). The implementation of this methodology resulted in total energy savings of 3.6%; most of the savings occurred in the formation area where monthly savings of 3 to 5% of the electricity used were saved, although how these savings were achieved in the formation area is not extensively discussed.

Lead-acid batteries are classified in Lighting, Starting, and Ignition (LSI) batteries (mainly used in the automotive sector), Traction batteries (for electrical vehicles), and Stationary batteries. About 385 million batteries (mostly LSI), accounting for a 41.5 billion USD market value, were marketed in 2010 (Miloloža 2013).

Battery manufacturing requires large amounts of heat and electricity to transform raw materials into the parts and components required in the manufacturing process. Additionally, sizable amounts of electricity are consumed by auxiliary systems (i.e., air compression system, assembly line, etc.) and also in the formation process (first charge of the battery) during the manufacturing (Jung et al. 2016; Pavlov 2011; Sullivan and Gaines 2010). Discussing the energy use in lead-acid battery manufacturing, Rantik (1999) showed that about 4.8 MJ of electricity, 1.67 MJ of heat, 0.14 MJ of liquefied petroleum gas (LPG), and 0.10 MJ of oil are used per kilogram of manufactured battery. The overall energy consumption from raw material production to finished battery, which depends on the use of either virgin or recycled materials, was estimated in the range of 15 to 35 MJ per kilogram of finished battery. Battery manufacturing uses between 5.8 and 8.9 MJ overall energy per kilogram of battery (Rydh and Sandén 2005; Sullivan and Gaines 2012) (i.e., between 16.6 to 59.3% of the overall consumption). In particular, the costs of electricity can account for over 90% of the energy costs of battery manufacturing (Wang et al. 2017). In total, battery formation accounts for over 50% of the electricity consumed for battery manufacturing (Jung et al. 2016; Sagastume et al. 2018), in some cases spiking up to 65% of the total electricity consumed (Wang et al. 2017). Therefore, an efficient use of electricity during battery formation is essential towards higher efficiency standards and lower economic costs.

This paper aims at developing new tools to assess, control, and manage the electricity efficiency within an EM of the formation process of LSI lead-acid batteries, based on the assessment of the operational parameters that are usually measured in battery plants and saved in databases.

Battery formation process

Lead-acid battery manufacturing consists of three steps (Dahodwalla and Herat 2000; Rantik 1999): grid manufacturing, battery assembly, and battery formation.

Grids for lead-acid batteries are made of a lead alloy and are produced either by lead casting in books molds or by continuous processes like stamping or extruding (Jung et al. 2016). Grid manufacturing mainly consumes heat (usually obtained from LPG or fuel oil) for lead melting and grid curing (Jung et al. 2016).

In the assembly process, battery components are assembled together, after which the battery is sealed and ready to receive the electrolyte (sulfuric acid). The main energy input is electricity (Jung et al. 2016).

After battery assembly, the formation process initiates. Battery formation is the initial charge of batteries. The electric charge in this process is used to transform the lead alloys in the positive and in the negative grids, into electrochemically active materials through chemicals transformations (Pavlov 2011).

Battery formation is essential for adequate battery performance and lifespan (Cope and Podrazhansky

1999; Thi Minh 2009; Pavlov et al. 2000; Petkova and Pavlov 2003).

Battery formation takes place in formation circuits, which include two subcircuits: an AC/DC rectifier and a batch of *N* batteries connected in series (Fig. 1).

The overall electricity consumed during battery formation depends on the number of batteries (*N*) simultaneously formed in the circuit, the voltage (V_{DC}) used in the process, and the electric charge (*C*) required by the battery model.

During battery formation, some heat is generated; a cooling system is used to maintain an adequate temperature. Therefore, during battery formation, the batteries connected in series (i.e., the batch of batteries subcircuit) are placed on cooling tables.

The current and the voltage used in the formation circuit affect both the electricity consumption and the battery performance and lifespan. Therefore, adequate selection and control of the current and voltage used in the formation circuit is essential for both the electric efficiency and the quality of the finished battery, aspects directly affecting the economic performance of battery plants.

Different algorithms are in use to control the current and voltage in the formation process. The Intermittent Charge Regime (ICR) is the most often used algorithm (Pavlov et al. 2000; Wong et al. 2008). It has two operation modes: constant current (CC) and intermittent current (IC), which are controlled using five control parameters: three voltage levels (V_{INI}, V_{IC1}, V_{IC2}) and two current levels (I_{IC1}, I_{IC2}) (see Fig. 1).

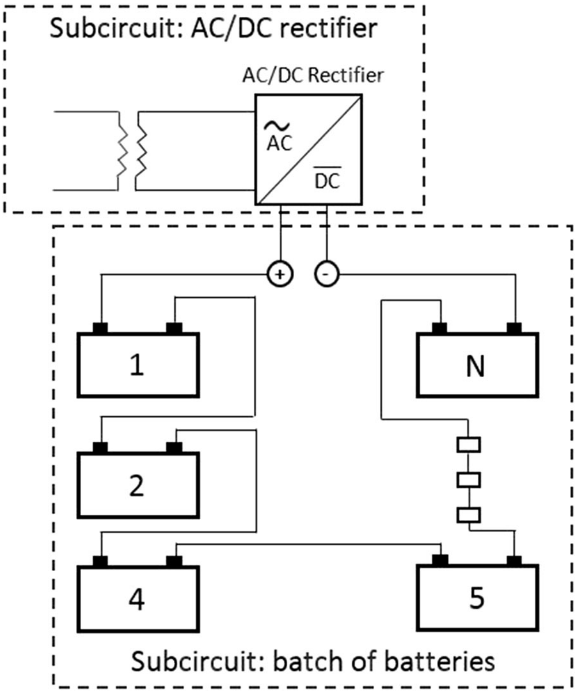


Fig. 1 Electric circuit for batteries formation

With the ICR algorithm (Fig. 2), the battery is charged to over 97% of its state-of-charge (SOC) in CC mode. This mode uses a constant current (CC) and stops when the voltage reaches the V_{IC1} value. Afterwards, the IC mode starts. In this mode, to reduce inner resistances and thus the temperature of endothermic reactions, the circuit opens when the voltage increases to V_{IC1}. With the circuit open, the voltage starts decreasing until the low control voltage (V_{IC2}) is reached, after which the circuit closes again. The open-close cycle continues until the battery is fully charged (i.e., 100% of the SOC). Regulated current pulses (I_{IC2}) (with a 30-s period) are used in this mode (Weighall 2003; Wong et al. 2008).

The energy efficiency of battery formation, defined as the ratio between the electricity actually used in the formation of a batch of batteries and the electricity supplied to the process, mainly depends on the technology used, the maintenance system, the operational staff, the operational standards, and the power quality in the AC supply network (Kiessling 1992).

The formation process usually includes a data acquisition system for the real-time measurement of different parameters (i.e., voltage, current, energy accumulated in batteries, electrolyte temperature in the battery, etc.). These data are usually saved in a database. The formation process algorithm is, however, specific to each battery model and the main control parameter, which defines the end of the formation process, is the ampere-hour accumulated in the battery (Chen et al. 1996; Pavlov et al. 2000).

The electric energy consumed in the formation of a batch of batteries is calculated as (Kiessling 1992):

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

where:

E_B—Electric energy consumed in the formation of a batch of batteries (Wh)

N—Number of batteries in the batch

V_{DC}—Voltage used in battery formation (varies between V_{INI} and V_{IC1}) (V)

C—Electric charge of the battery model (Ah)

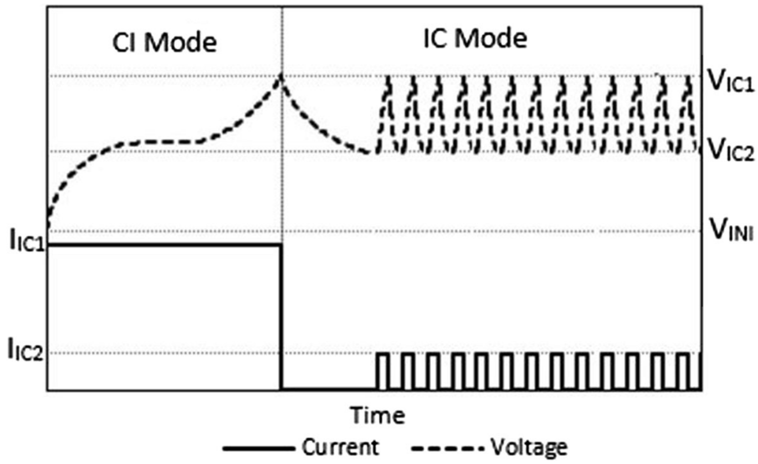


Fig. 2 ICR algorithm: current and voltage variations

As consumption of electricity in battery formation is high and it influences both the production costs and the quality of finished batteries, it must carefully be controlled (Kiessling 1992; Jung et al. 2016).

Most of the electricity supplied to battery formation is transformed into chemical energy stored in the battery; the rest is lost because of the heating resulting from chemical reaction between the grids and the electrolyte, or consumed in the decomposition of water into oxygen and hydrogen. In addition, some energy is lost because of heating of circuit components such as wires and connectors. The electricity supplied to the formation process is thus given by:

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

where:

E_T—Electricity supplied to the formation circuit (Wh)

E_{BF}—Electricity used by batteries in the formation process (Wh)

E_{LB}—Energy loss within batteries during battery formation because of the exothermal chemical reactions that cause heat loss and the formation of H_2 and O_2 (Wh)

E_{LWC}—Energy loss in the wires and connectors of the formation circuit (Wh)

E_{LR}—Energy loss in the AC/DC rectifier (Wh)

Most of ET is used in the batch of batteries subcircuit (EBB) and is given by:

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

E_{BF} has a similar value for each battery model, while E_{LB} and E_{LWC} depend on the operational factors and the technical state of the circuit components. Among others, the voltage and current output of the AC/DC rectifier is measured during battery formation process, to control de ICR algorithm. Based on this measure, the energy used in the batch of batteries subcircuit (E_{BB}) can be calculated and used to assess the energy losses in the formation of a batch of batteries (Ponce and Moreno 2015):

$$E_{BB} = \int_0^{t_1} p(t)\cdot dt = \int_0^{t_1} V_{DC}(t)\cdot I_{DC}(t)\cdot dt \quad (4)$$

where:

$p(t)$—Instant power (W)

V_{DC}—Voltage in the power line of the battery subcircuit (V)

I_{DC}—Current in the power line of the battery subcircuit (A)

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

Based on the calculation of E_{BB}, an energy performance indicator (EnPI) of battery formation is proposed (i.e., the ratio between E_{BB} and battery production). Based on the EnPI, which is calculated for each formation process in the database, an energy baseline (EnB) is developed for each formation circuit. Using both the EnPI and the EnB is possible to assess the real-time inefficiencies, thus allowing the implementation of rapid corrective actions towards higher efficiency standards (Cabello et al. 2016).

In general, directly measuring the electricity consumption in the formation circuits is both expensive and complicated. Thus, a soft sensor (SS) is developed to calculate E_{BB}.

Literature review

Soft sensors

Measuring and monitoring process parameters with adequate instrumentation is essential to control industrial processes, in order to guarantee optimum and safe operations. However, some parameters are difficult or too expensive to measure. In these cases, different approaches like SS are used. SSs use process parameters measured with the available instrumentation to calculate or estimate process parameters to difficult or too expensive to measure.

There are two types of SS:

1. Model-driven: based on mathematical models describing the development of a process. These SSs are most widely applied in the design and planning of industrial process facilities (Kadlec et al. 2009).
2. Data-driven: based on data directly measured in a process describing the real conditions. These SSs are most widely used to monitor, control, and improve process performance (Wang et al. 2010).

One main application of SSs in process monitoring is to detect deviations from standard operation, aiding to identify the causes. For this application, SSs are usually based on univariate or multivariate statistic methods applied to the historic data of a process to define a relevant set of representative features supporting the process of decision-making (Kadlec et al. 2009).

Data-driven SSs use inferential models based on process parameters directly measured. In simple processes, where models are available or easy to obtain, a regression analysis is often enough (Lin et al. 2007; Kadlec et al. 2009). Moreover, for complex systems in which the process mechanisms are not fully understood, empirical models (i.e., neuronal networks or multiple regression analysis) are used to derive the correlation between variables (Wang et al. 2010).

Data-driven SSs have been successfully implemented in energy consumption assessment and EM of several technologies and facilities (Velázquez et al. 2013).

Several applications of SSs to improve the EE of buildings have been described. Thanayankizil et al. (2012) used an SS to estimate the occupancy rate in rooms of an office building to improve the EE. Li et al. (2014) developed an SS to assess in real-time, the dynamic cooling load for different reference temperatures in buildings. To assess heat consumption in buildings at room level, Ploennigs et al. (2011) proposed an SS based on measuring the temperature with a temperature sensor, which guarantees thermal comfort while optimizing EE and reducing the monitoring costs.

Moreover, some applications to steam boilers have been discussed. Hadid et al. (2014) developed an SS to assess the fuel consumption in a 750-kW industrial boiler. The SS uses a linear model based on pressure and temperature as control variables and a Gaussian nonparametric model to calculate the mass flow of gas with a relative error of 3.5%. In a different application, Qi et al. (2015) developed an SS, based on a predictive control model, to assess and control steam quality of an industrial boiler, resulting in a reduction of its energy intensity. Moreover, to assess the fuel quality in industrial boilers, Zhao et al. (2015), and Kortela and Jämsä-Jounela (2012) developed two SSs, based on operational parameters measured in the exit gases. Results show that both SSs can be used to optimize the control systems and, thus, the combustion processes.

Some applications have also been developed for electric systems. Zhang et al. (2008) developed an SS to measure significant parameters, which cannot be directly measured, to control synchronous generators (e.g., power angle and current of the stator circuit). In an application to an electric system, Najar et al. (2015) developed an SS to monitor the thermal performance of electric transformers and the energy balance between the low and middle voltages in High-Voltage (HV)/Middle-Voltage (MD) substations in smart grids. The SS is based on data measured by a smart meter installed in the Low-Voltage substation.

Leonow and Mönnigmann (2014) replaced an expensive flowmeter used in low-speed radial pumps with a SS to calculate the flow in real-time. Moreover, Järvisalo et al. (2016) developed an SS, based on real-time monitoring of the specific energy consumption, to save electricity in air compressors. Results show that the adequate application of this SS can save energy as compared to the traditional load/unload control scheme.

In general, different approaches exist to develop SSs (Hong et al. 1999; Kalos et al. 2003; Warne et al. 2004; Fortuna et al. 2005; Gomnam and Jazayeri-rad

2013; Chowdhury 2015). Specifically for batch industrial processes, Kadlec et al. (2009) proposed the following methodology.

1. Data inspection: a first inspection of data is developed to assess availability, trends, and accuracy. Adittionally, a target variable is defined assessing which regression model is needed (i.e., simple regression model, complex regression model or neural network).
2. Selecting historical data: focuses on selecting random data, which will be used to develop the model to be used in the SS.
3. Data pre-processing: iterative step, repeated until the data is considered ready for use in the evaluation of the model. It aims at identifying missing data, detection and handling of regular data, selection of the important variables of the process.
4. Model selection and validation: since mathematical models are the cornerstone to SSs, their adequate selection is essential. Usually, the model type and its parameters are specifically selected for each SS. A simple procedure is to start with simple models (e.g., linear regression) and, if needed, gradually increase model complexity until adequate results are obtained (Friedman et al. 2001).

After the SS is developed, an evaluation using independent data should be carried out. The Mean Square Error method, which quantifies the mean square distance between the calculated value and the real value (Schluchter 2014), is used to this end.

Energy management methodology

Energy management entails all the actions to reduce energy consumption and its costs (Vesma 2009). The successful implementation of an EM strategy requires the knowledge of the energy consumption and of how, where, and when energy is consumed. In different industrial sectors, saving potentials of 10 to 30% of the energy consumption have been identified, with significant cost reductions associated, frequently without requiring large investments (McKane et al. 2008).

An EM methodology is a systematic approach for continuous improvement of the energy performance, providing an institutional framework to manage energy consumption and to identify saving opportunities (Worrell 2011). In companies without a clear energy policy, the development of energy efficiency projects and the implementation of EM strategies and tools proved effective to identify and realize energy saving opportunities (Goldberg et al. 2011; Cabello et al. 2016).

ISO 50004 and 50006 (ISO 2012; 2014) offer guidance for the implementation, maintenance, and improvement of EM systems, based on the use of Energy Baselines (EnB) and Energy Performance Indicators (EnPI) as a measure of the energetic performance. In this study, the procedure defined in the ISO 50001 standard (ISO 2011) is used as a starting point in the EM methodology developed for the battery formation process:

1. Statistical analysis of the historic database: assess the correlation between electricity consumption and battery production and propose an effective EnPI.
2. Identify the main parameters affecting the energy efficiency of battery formation and assess their influence based on the statistical analysis of the historical database.
3. Develop tools for the real-time monitoring of the electricity consumption in battery formation.
4. Validate and implement the developed tools.
5. Identify saving opportunities and implement adequate measures to realize them.

Energy efficiency assessment of battery formation

The EM methodology is applied to a battery plant in Barranquilla, Colombia. In this factory, battery production increased at a yearly average of 14% between 2012 and 2014, and electricity consumption showed a similar trend. Improving the electric efficiency is essential to reduce the battery production costs.

The formation section consumed about 53% of the overall electricity of the battery plant. There are 204 formation circuits, which in all cases use the ICR algorithm (see Fig. 1). Each circuit includes a subcircuit for forming a batch of 18 batteries. In total, the formation of a batch of batteries takes 18 to 26 h. The batch of batteries is placed on 12 cooling tables (18 circuits per table). The formation section operates 24 h 7 days a week, with short stops for cleaning and maintenance. Overall, 168 battery models, with capacities varying between 160 to 735 Ah, are produced in the plant.

The energy efficiency assessment (step 1 of the EM methodology) is conducted using production data from July 2014 and July 2015.

Given the significant differences between the capacity and size of the different battery models manufactured in the plant, the concept of equivalent production, introduced by ISO (2014) is applied, introducing the equivalent battery production ($P_{\mathrm{eq-b}}$):

$$P_{\mathrm{eq-b}} = P \cdot k_{\mathrm{b}} \tag{5}$$

where:

P—Battery production (units)

k_{b}—Battery capacity coefficient

The battery capacity coefficient is calculated as:

$$k_{\mathrm{b}} = \frac{C_{\mathrm{b}}}{C_{\mathrm{bmin}}} \tag{6}$$

where:

C_{b}—Capacity of the battery model (Ah)

C_{bmin}—Capacity of the smallest battery (Ah)

In this case, the EnPI proposed to assess the formation of each batch of batteries is:

$$\mathrm{EnPI} = \frac{E_{\mathrm{BB}}}{P_{\mathrm{eq-b}}} \tag{7}$$

This EnPI is useful to assess the EE of each batch of batteries formed, independently of the battery model. Moreover, it can be used for comparative studies to define the parameters affecting the EE.

Between July 2014 and July 2015, there are 55,000 formation batches (of 18 batteries each, for 168 models) in the database. A random sample of 2902 batches, for a 98% confidence interval, is used to develop the EM tools. The EnPI was individually calculated for each of the selected batches.

To avoid the influence of outliers, the data is sieved using the Hampel identifier method which applies the median absolute deviation from the median (MAD), as also applied by Lin et al. (2007):

$$\mathrm{MAD} = 1.4826 \cdot \mathrm{Mk} \tag{8}$$

with:

$$\mathrm{Mk} = \mathrm{median}\left\{X_1 - X^*,\ X_2 - X^*, \ldots, X_n - X^*\right\} \tag{9}$$

n—Number of data points

$X_{1,2,3,\ldots,n}$—Raw data points

$$X^* = \mathrm{median}\{X_1, X_2, \ldots, X_n\} \tag{10}$$

The out of the range data ($X < \left(\overline{X} - \mathrm{MAD}\right)$, $X > \left(\overline{X} + \mathrm{MAD}\right)$) is identified as an outlier and removed from the dataset. In total, 68 outliers were identified (i.e., 2.3% of the sample data). The outliers, in agreement with Kadlec et al. (2009), were mainly resulting from sensor malfunctioning.

Parameters affecting the energy efficiency of battery formation

To identify saving opportunities to improve the EE of battery formation, the main parameters affecting electricity consumption must be identified. To this end, several interviews were conducted with the operational staff of the formation section. In addition, a literature review and a technical assessment of the formation process were carried out. Results are summarized in a fishbone diagram (Fig. 3).

Influence of technology on the EnPI

To assess the influence of technical conditions of the formation circuit on the energy efficiency of battery formation, the EnPI of more than 55,000 processes registered from July 2014 to June 2015 was calculated (for 204 formation circuits).

The tests of Bartlett to variance verification were applied to assess whether or not the standard deviations of the sets of EnPI values corresponding to the different circuits differed significantly. Results showed that there were no significant differences (at the 95% confidence level) between the standard deviation of the sets of EnPI of the different circuits. Moreover, to evaluate if there were significant differences between the mean values of the sets of EnPI of the different circuits, Fisher's least significant difference (LSD) test was applied. Results showed that there were some differences (95% confidence level) between the mean EnPI values: 8 circuits had a significantly lower EnPI value (better performance) and 7 circuits with had a significantly higher EnPI value (poorer performance) than the average. A detailed electricity review in each circuit to identify the factors causing the differences was carried out for each circuit.

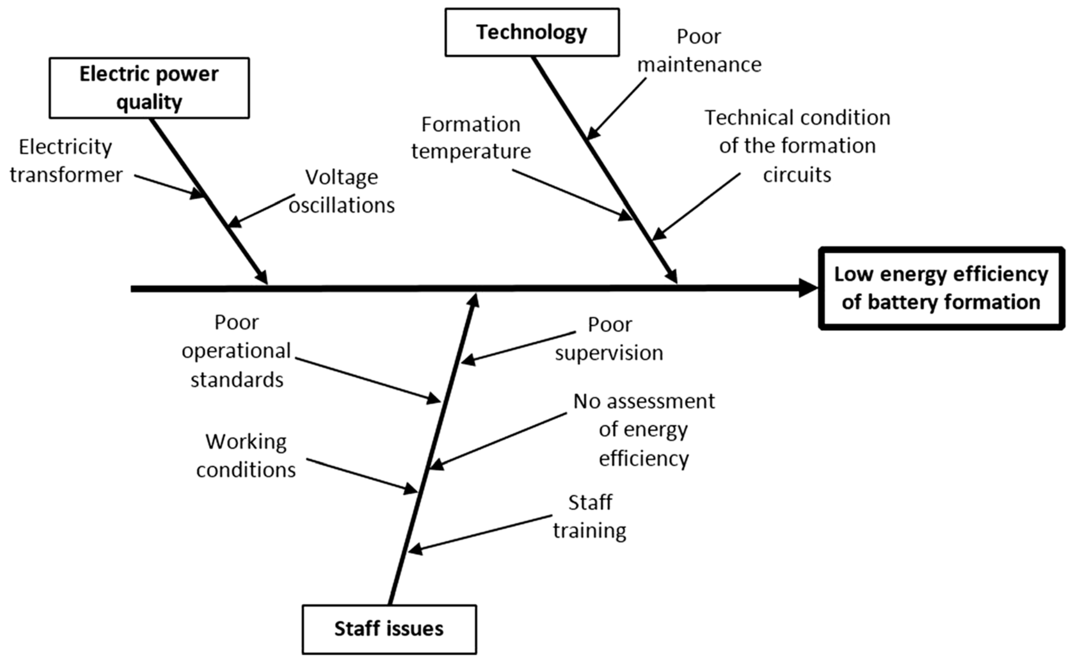


Fig. 3 Parameters affecting the energy efficiency of the battery formation process

Influence of the operational staff on the EnPI

The formation section operates 24/7 with five operator teams working in 12-h shifts (two teams per day) and 36 h a week. The 12-h shifts start at 5 am and 5 pm, respectively. In order to assess the influence of fatigue of the staff on the energy performance, the starting time of formation processes was sorted as shown in Table 1.

Each team includes one supervisor, who oversees the operational practices during the setting of the batches of batteries in the circuits, prior to the start of battery formation. In order to guarantee the quality of the formed batteries, the supervisor controls the parameters and operation of battery formation (e.g., by setting the formation process algorithm), keeps track of the production rate, and oversights battery handling during the setting of the batches of batteries in the circuits (i.e., prior to the start of battery formation). Meanwhile, the energy consumption and factors like the technical conditions of wires and connectors and their maintenance are not oversight. In the plant, the supervisor efficiency depends on the quality control of the formed batteries, while the energy consumed during battery formation does not affect its performance evaluation. One particularity of this process during the period analyzed was the fluctuation of the operators in the different teams, while the supervisors remained. Therefore, considering that the main staff influencing the outcome of battery formation is the supervisor by setting and oversighting the operational practices used by the team operators, the analysis focuses on its influence in the EnPI.

Table 1 Interval of the analyzed formation process starting time

Shift	Start time	End time
1	5 am	11 am
2	11 am	5 pm
3	5 pm	11 pm
4	11 pm	5 am

Another staff-related parameter affecting the EnPI is the formation pocesses starting hour (see Table 1), which influences the fatigue of both operators and supervisors, thus affecting the operational practices of the team. Therefore, based on the database information, a statistical analysis was carried out to highlight the influence of both parameters on the EnPI. Both parameters are included in the database of the process. For the statistical assessment was considered 1 year of data (July 2014 and June 2015), with 55,500 formation processes included, during which no changes of supervisor occurred. Additionally, the formation processes were organized in four groups according to their starting hour.

The same statistical approach used in "Influence of technology on the EnPI" is used here. The test of variance verification was applied, to assess the differences in the standard deviation of the sets of EnPI values corresponding to each supervisor, thus, establishing if the data sets are comparable between each other. Results showed that there are no significant differences (at 95% confidence level), between the standard deviation of the sets of EnPI values. Moreover, to evaluate if there are significant differences between the mean values of the sets of EnPI values corresponding to each supervisor Fisher's LSD test was applied. Results showed significant differences (95% confidence) between the mean EnPI values. From these results, it can be concluded that the supervisor and the starting hour of battery formation influences the EnPI.

Saving opportunities

The circuits identified in "Influence of technology on the EnPI", with the lowest and highest EnPI values were evaluated in detail to identify the causes of inefficiencies in the formation section. To this end, the energy loss in the connection lines and in the wires and connectors of the battery batch subcircuit was measured. Each measure was repeated 10 times on each of the circuits selected for the assessment.

To compare on the same basis, the measurements in the different circuits were carried out during the formation of the same battery model. Results showed that the average energy loss between the best and the worst formation circuit differ by about 3 kWh. This difference results from the use of wires and connectors in poor technical conditions on the worst circuits, which is confirmed by a thermographic assessment of the formation circuits presents the thermographic assessment of one circuit. This shows that wires and connectors in good technical conditions operate at around 45 °C, while the ones in poor technical conditions operate at temperatures up to 94.8 °C (see Fig. 4). Therefore, wires and connectors in poor technical conditions increase the electrical resistance in the circuit increasing the electricity consumption of battery formation. This point to significant saving opportunities requiring the implementation of different measures:

- Assess regularly the formation circuits
- Establish a procedure to certify the technical condition of wires and connectors
- Clean the surface of connectors before using them in the formation process
- Improve the maintenance system of the formation circuits to avoid inefficiencies on wires and connectors
- Redesign connectors
- Establish 8-h work shifts instead of the actual 12-h work shifts

Another source of inefficiencies is detected in the voltage used in the formation process, which averages 17.6 V (i.e., higher than the maximum of 16 V recommended for this process (Kiessling 1992; Prout 1993; Pavlov 2011)). From Eq. 3, the electricity consumed is directly proportional to both, the voltage (V) and the

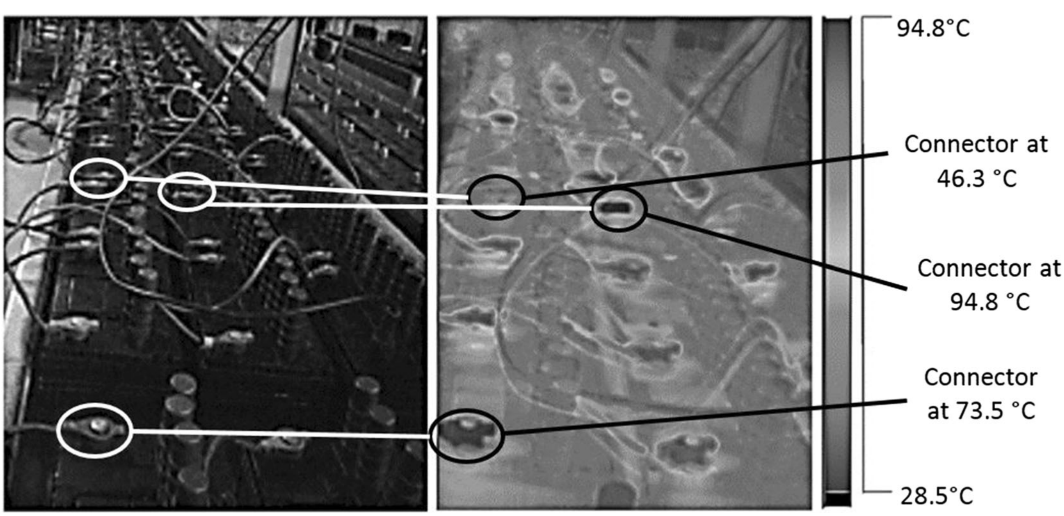
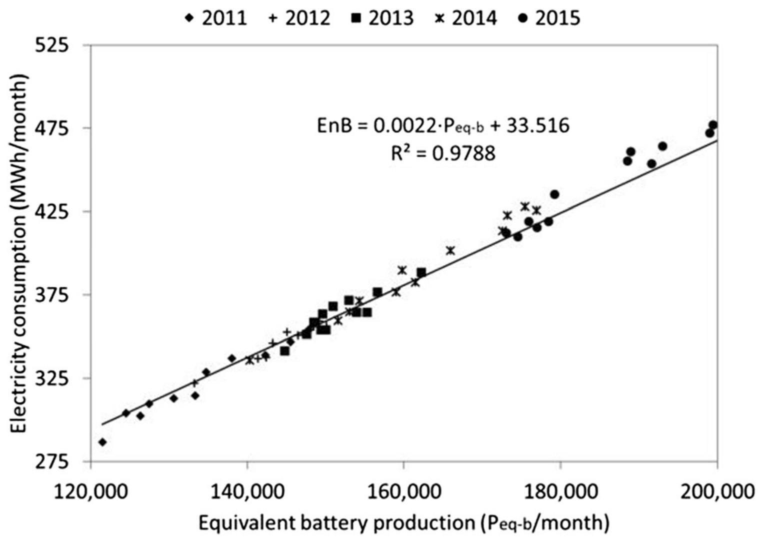


Fig. 4 Thermographic assessment of a battery batch subcircuit

Fig. 5 Monthly EnB of the formation section



electric current (A). As the formation algorithm operates at constant current and the internal resistance of the batteries is almost constant for batteries in the batch, the use of higher voltages results in higher electricity consumption. Aside from the energy loss, the excess of electricity consumed increases the production of H_2 and O_2 (IEC 60095-1: 2000; Pavlov 2011), the output voltage of the transformers was adjusted to the minimum possible (16.4 V), which is closer to the recommended value.

Energy management tools

Assessing the EnPI of the battery formation section is the first step towards the development of EM tools. Figure 5 shows the correlation between the monthly electricity consumption and the monthly equivalent batteries produced of the formation section (with data from 2012 to 2015). From the correlation is obtained the monthly EnB of the formation section is obtained.

The high correlation ($R^2 = 0.97$) obtained for the EnB proves the usefulness of the EnPI. Furthermore, the EnB obtained is useful to forecast the monthly electricity consumption of the formation section and, thus, to assess its overall electricity performance.

A tool for the control of the electricity consumption in the formation section at circuit level is needed, on the one hand, because of the differences in the technical state of the different formation circuits, which influences the EnPI of battery formation, and, on the other hand, because the formation circuits are used on a daily basis so that rapid corrective action is necessary to reduce the

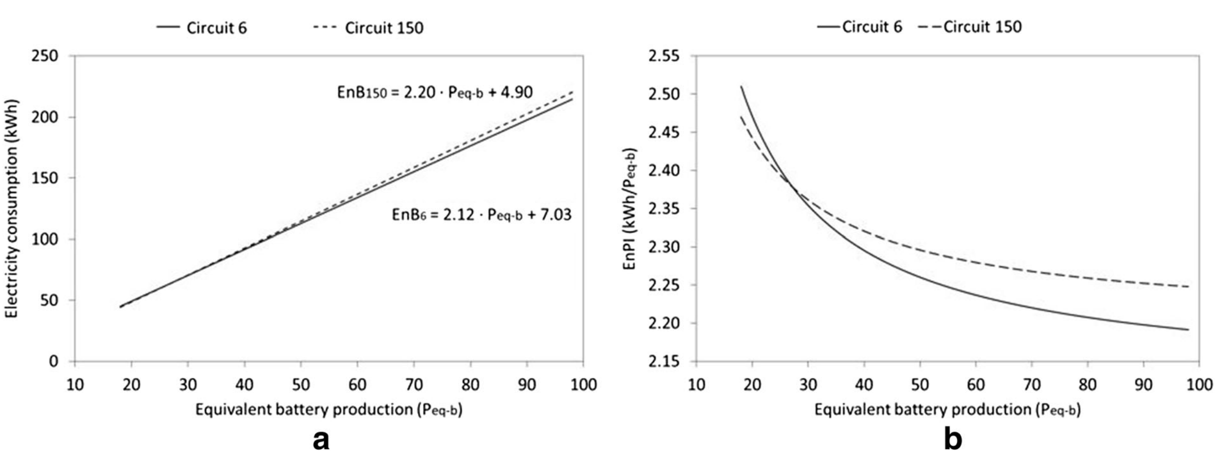


Fig. 6 Energy management tools for two formation circuits

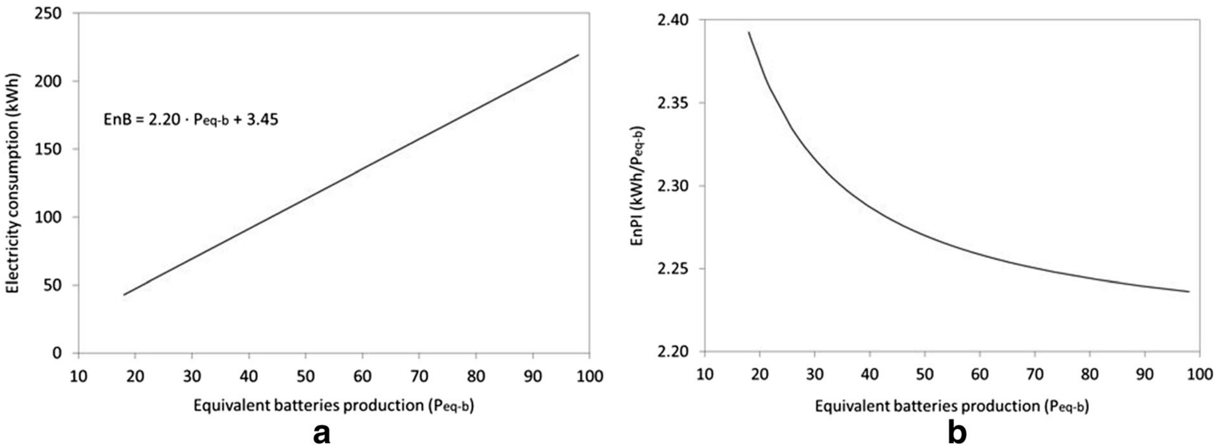


Fig. 7 Energy management tool for the operational staff teams

electricity consumption. Figure 6 shows an example of the control tools developed to assess the electricity consumption at the circuit level for each batch, for two specific circuits.

These tools allow rapid detection of inefficiencies at the circuit level. Additionally, they can detect the malfunctioning of the sensors used to control the ICR algorithm.

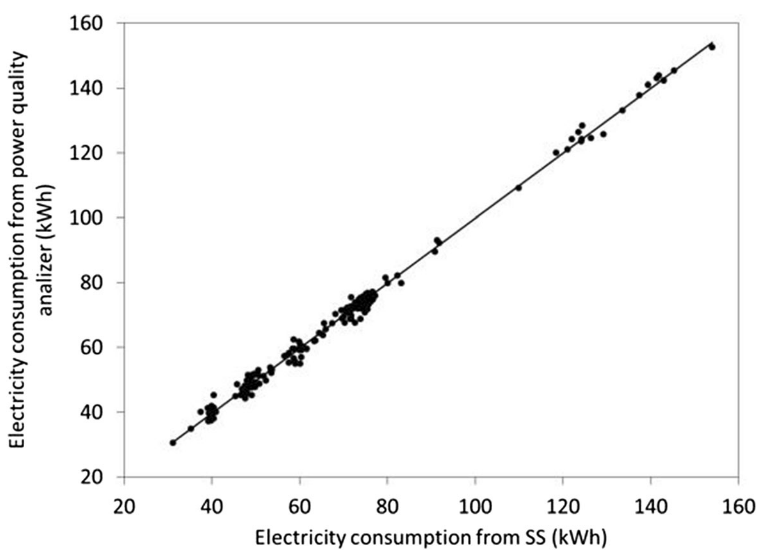
Similarly, for the rapid detection of malpractices and issues associated with the operational staff, control graphics are developed to assess the trends of the EnPI of the operational staff (see Fig. 7).

The figure shows EnB and the control graph constructed for the supervisor whose processes of formation were developed with better energy efficiency. These tools are used to assess the electricity consumption efficiency associated with the different work teams, permitting the rapid detection of negative trends of the EnPI associated with malpractices of the employees.

Soft sensor for the electricity consumption of battery formation

There are 204 formation circuits in the formation section. Given that measuring devices for the real-time monitoring of the electricity consumption in each circuit are both expensive and complicated, a SS is developed, based on the different parameters measured in real-time to control the ICR algorithm. The SS is designed to calculate the electricity consumption and the EnPI of

Fig. 8 Scatter plot: power quality analyzer measures vs. SS measures



the formation circuits.The methodology described in "Battery formation process" is used to develop the SS, which is validated using the approach of Qi et al. (2015). This approach is based on direct measurement of the parameter to be calculated by the SS and compares its dispersion with respect the values measured by the hard sensors.

A power quality analyzer is used to directly measure the electricity consumption in the formation process of 170 batches for 5 different battery models in 17 formation circuits. For these batches, the electricity consumption is also measured with the SS. The results are compared in a scatter plot (Fig. 8).

Results show a strong linear correlation (R^2 = 0.99) between the measures with the power quality analyzer and the SS estimated value. The mean absolute error is 1.55 with a standard deviation of 1.93. These results

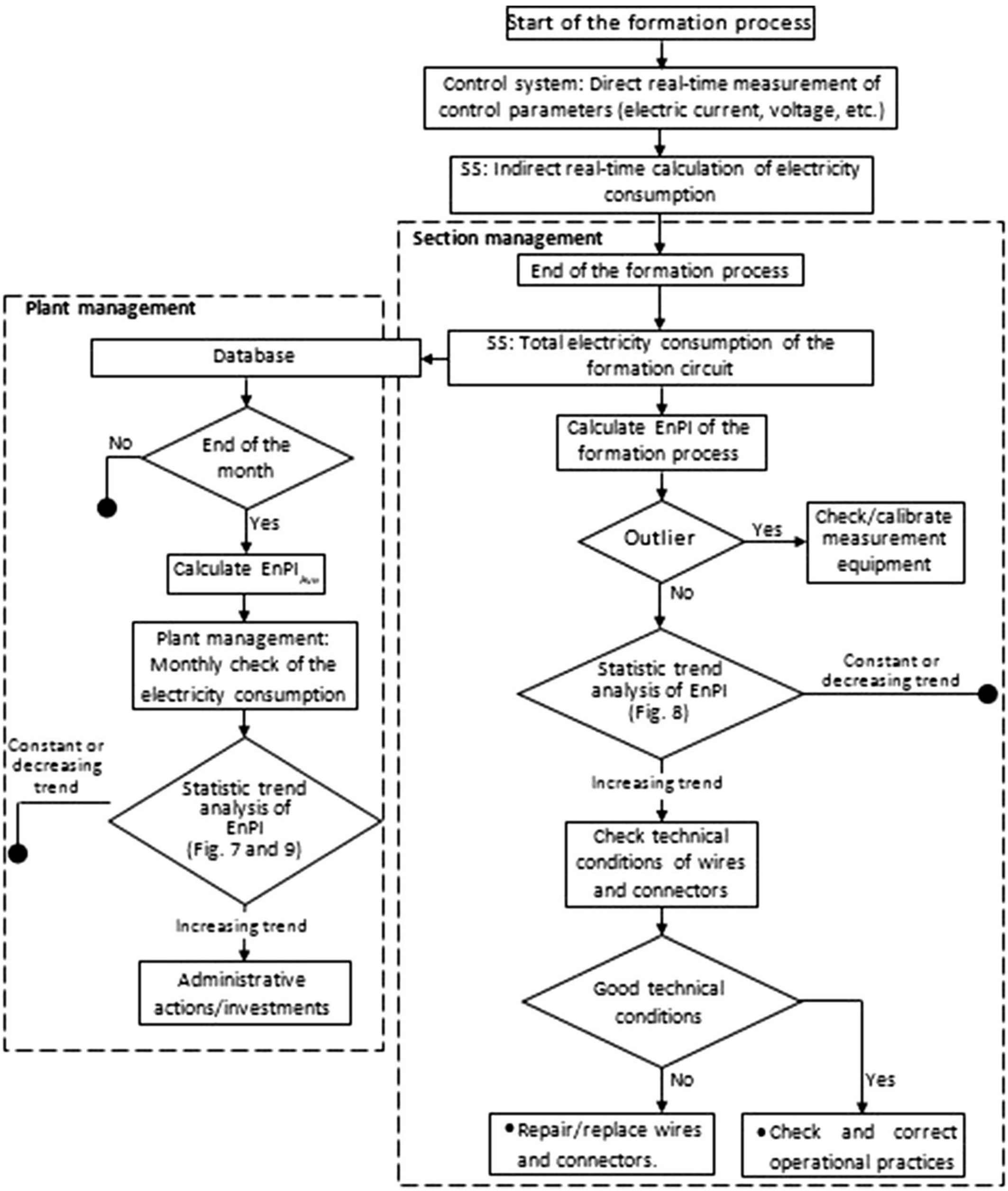


Fig. 9 EM methodology of the battery formation section

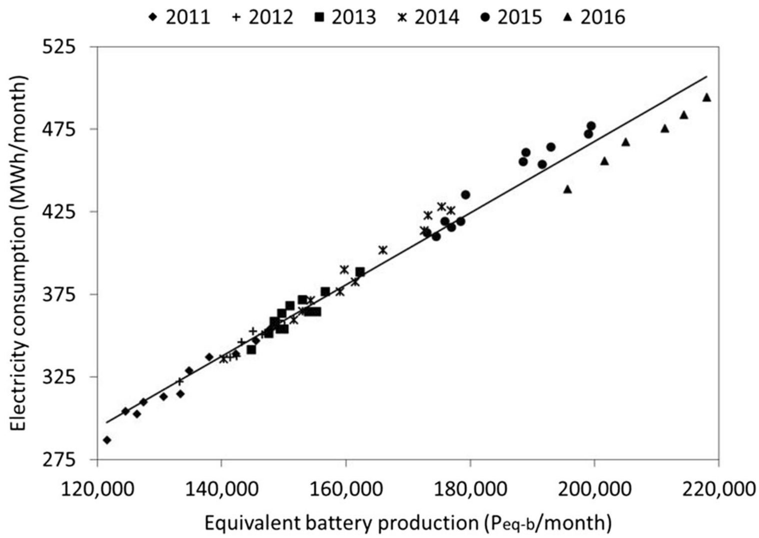


Fig. 10 Monthly electricity consumption of the battery formation section

validate the accuracy of the SS to measure the electricity consumption in the formation circuits.

Results and discussion

Results

The EM actions of the proposed methodology were applied in the formation section, starting in January 2016, during 6 months. Results showed a reduction of the electricity consumption during this period.

The EM procedure, developed to implement the EM tools in the battery formation section is shown in Fig. 9. The developed tools are applied at two levels: plant level and section level.

Considering the trend analysis of the monthly average ($EnPI_{aver}$, see Fig. 10) of the formation process, the electricity consumption is assessed on a monthly basis, in the general meeting of the plant management. Based on the trends (increasing, constant, or decreasing), the plant management decides which actions/investments are needed to improve or maintain the energetic performance of the formation section. Figure 10 shows the monthly electricity consumption from 2011 to 2016. The results of the implementation of the EM tools, developed in "Conclusions," to the formation section are compared with the previous performance of the section.

Results show that regardless of the increasing trend of both, the battery production and the electricity consumption, the energy performance of section improved as a result of the implementation of the EM tools. Table 2 shows the results of the implementation.

Comparing the electricity consumption during the implementation of the EM tools (EC: Measured) to the

Table 2 Results of the EM tool implementation during 2016

Month	Battery production	P_{eq-b}	EC: EnB (MWh)	EC: measured (MWh)	Electricity saving (MWh)	Electricity saving (%)
January	113,693	204,994	484.5	467.2	17.2	3.6
February	105,971	201,604	477.0	455.8	21.2	4.4
March	109,503	217,982	513.1	494.4	18.7	3.6
April	121,108	214,352	505.1	484.0	21.1	4.2
May	100,242	211,275	498.3	475.6	22.7	4.5
June	938,40	195,613	463.9	438.7	25.1	5.4
Total	644,357	1,245,820	2941.9	2815.8	126.1	4.3

EC electricity consumption

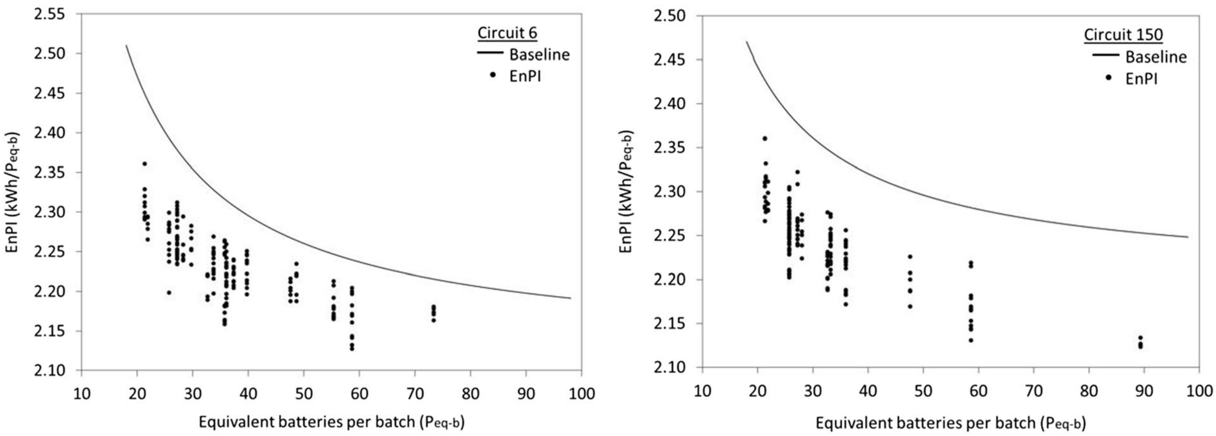


Fig. 11 EnPI of the formation batches in circuits 6 and 15 for 2016

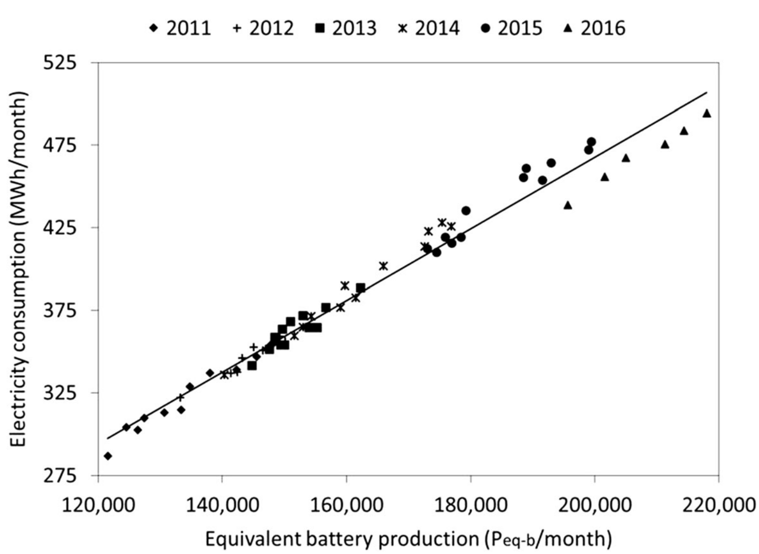
EnB predictions (EC: EnB) shows an average reduction of the electricity consumption of the formation section by 4.3% (varying between 3.6 and 5.4%). In total, a reduction of 126 MWh as compared to the EnB was achieved during the 6-month implementation period (with monthly reductions of 17 to 25 MWh). This shows that the EM tools improved the energetic performance of battery formation, reducing the production costs. However, there are other improvement opportunities as shown in Fig. 11 for two of the formation circuits.

In both circuits, the variability of the EnPI during the formation of different batches of the same battery model points to further saving opportunities. In future studies, the AC/DC rectifiers must be included in the assessment, to identify the energy losses associated with this component.

Discussion

The energy efficiency of battery manufacturing is a cornerstone for its economic costs and its quality standards (Sagastume et al. 2018). Additionally, the adequate control of the electricity consumed during battery formation is fundamental for its quality and lifespan (Duarte et al. 2017). However, most battery-related studies focus on discussing the potentialities of new materials, new battery technologic developments, battery applications (i.e., in electric or conventional vehicles, in energy storage applications, etc.), and some specific processes of manufacturing (e.g., charging, discharging, and equalization of battery formation), rather than discussing the energy use and control of battery manufacturing. The studies of Wang et al.

Fig. 12 Electricity consumption vs equivalent battery production



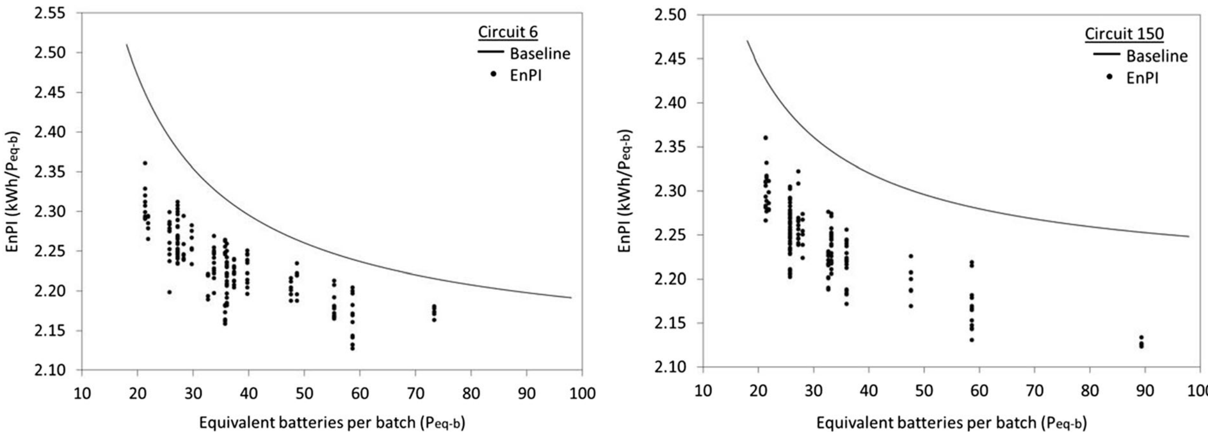


Fig. 13 Equivalent batteries per batch

(2015) and Wang et al. (2017) focused on lowering the costs of electricity at plant and at battery formation levels. In both cases, the optimization can result in lower costs of electricity (i.e., by reallocating the power loads in lower time-of-day electricity prices), without actually reducing the energy consumption. In particular, optimizing the process of battery formation following Wang et al. (2017) can result in current overload because of the reallocation of the highest power loads of the circuits to the lower time-of-day electricity prices. Thus, the optimization should consider all the formation circuits of the area, rather than just one circuit. Moreover, Sagastume et al. (2018) focused more on the control and management of the electricity consumption at the battery plant level, than at the formation area level.

Overall, this study shows how to implement an energy management strategy, based on a soft sensor, to effectively reduce and control the electricity used during battery formation. Since the soft sensor proposed uses the standard automation required to control the formation process, it can be introduced with low investments. This approach permits to individually (i.e., at formation circuit level) and globally (i.e., at formation area level) control and manage the electricity consumption of the battery formation process (Figs. 12 and 13).

Conclusions

The formation process accounts for over half of the electricity consumption in the manufacturing of lead-acid batteries. The EM methodology proposed in this study is based on a SS, which is a cost-effective alternative to measure the electricity consumption of battery formation. This methodology permits to rapidly detect inefficiencies in the formation circuits, related with either the technical condition of the formation circuits or the operational staff. The proposed EnPI permits to assess the energetic performance of battery formation at both, the formation section and the plant management level.

Results show that although the plant overall electricity consumption increased as a result of the increasing battery production, the specific consumption per battery was reduced, thus improving the energetic performance of the plant. In total, the implementation of the EM methodology resulted in an average reduction of the electricity consumption of the formation section of 4.3% for the 6-month period assessed.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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