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

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

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Conflict of interest: the authors declare that they have no conflict of interest

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1. Introduction

The energy saving potential of the industrial sector is around 974 million ton 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; Palamutcu, 2010; Poscha et al., 2015; Rudberg et al., 2013), there is need for more adequate methods and tools for a more comprehensive assessment of energy efficiency (EE) (Giacone and Mancò, 2012; Bunse et al., 2011). In addition, Weinert et al. (2011a) 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, to the best knowledge of the authors, there are in the specialized literature no studies discussing energy consumption and management of lead-acid battery manufacturing.

Lead-acid batteries are classified in Lighting, Starting and Ignition (LSI) batteries (mainly use 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, where 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., 2015; 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 kg of manufactured battery. The overall energy consumption from raw materials 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 kg of finished battery. Battery manufacturing uses between 5.8 and 8.9 MJ overall energy per kg of battery (Rydh and Sandén 2005; Sullivan and Gaines 2012) (i.e. between 25 to 38 % of the overall consumption). Reducing the electricity consumption used in battery formation is thus essential towards reaching higher efficiency standards.

This paper aims at developing new tools to assess, control and manage the electricity efficiency within 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.

2. Battery manufacturing

Lead-acid battery manufacturing consists of three steps (Rantik, 1999; Dahodwalla et al., 2000): 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 (sulphuric 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 et al., 1999; Thi Minh, 1999; Pavlov et al., 2000; Petkova and Pavlov, 2003). The formation process consumes large quantities of electricity, accounting for over 50% of the overall electricity consumed during battery manufacturing (Jung et al., 2016).

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).

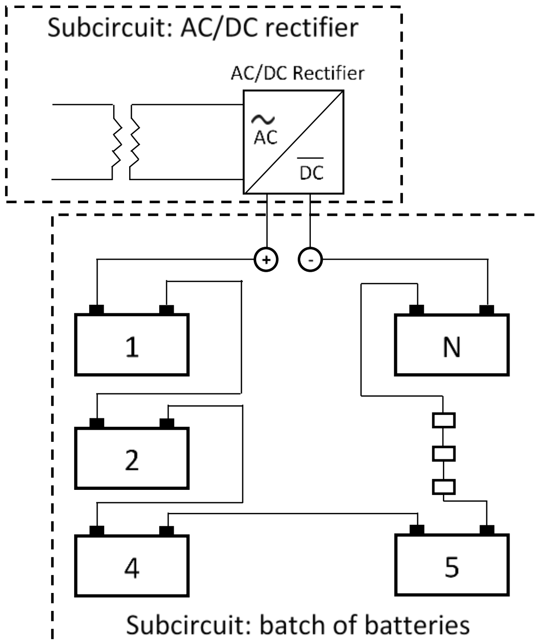

Fig. 1. Formation circuit.

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. 2).

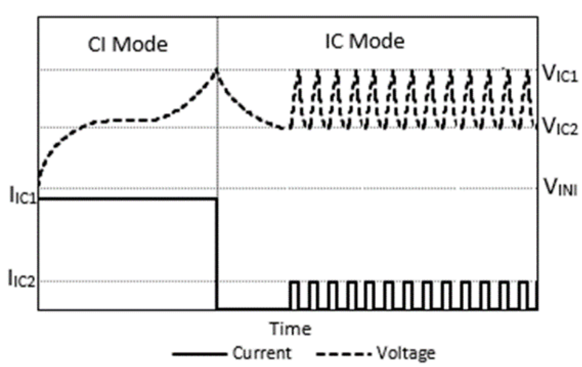

Fig. 2. ICR algorithm: current and voltage variations.

With the ICR algorithm, 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 reach 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 is 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):

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

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)

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 loss because of heating of circuit components such as wires and connectors. The electricity supplied to the formation process is thus given by:

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

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:

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

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):

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

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 equation 4, a numerically 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 to implement rapid corrective actions toward 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 to calculate E_{BB}.

3. 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 SS 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 SS 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 SS 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 SS 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. (2013) 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 that, which cannot be directly measured, to control synchronous generators (e.g. power angle, current of the stator circuit, etc.). 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 et al. 2015). Specifically for batch industrial processes, Kadlec et al. (2006) 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: focusess 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 be 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 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.

4. 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 (Worrel, 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; ISO, 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 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.

5. Case study

The EM methodology (see section 4) is implemented in 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 takes18 to 26 hours. The batch of batteries is placed on 12 cooling tables (18 circuits per table). The formation section operates 24 hours 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.

5.1 Energy efficiency assessment.

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_{eq-b}):

$$P_{eq-b} = P \cdot k_b \qquad (5)$$

where:

P – Battery production (units)

k_b – Battery capacity coefficient

The battery capacity coefficient is calculated as:

$$k_b = \frac{C_b}{C_{bmin}} \qquad (6)$$

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:

$$\text{EnPI} = \frac{E_{BB}}{P_{eq-b}} \qquad (7)$$

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 2,902 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 apply the median absolute deviation from the median (MAD), as also applied by Lin et al. (2007):

$$\text{MAD} = 1.4826 \cdot \text{Mk} \qquad (8)$$

with:

$$\text{Mk} = \text{median}\{X_1 - X^*, X_2 - X^*, \dots, X_n - X^*\} \qquad (9)$$

n – Number of data points

$X_{1,2,3,\dots,n}$ – Raw data points

$$X^* = \text{median}\{X_1, X_2, \dots, X_n\} \qquad (10)$$

The out of the range data ($X < (\overline{X} - \text{MAD})$, $X > (\overline{X} + \text{MAD})$) is identified as an outlier and removed from the dataset.

Figure 3 shows the dataset analyzed. In total, 68 outliers were identified (i.e. 2.3 % of the sample data). The outliers, in agreement with Kadlec et al. (2009), mainly resulting from sensor malfunctioning.

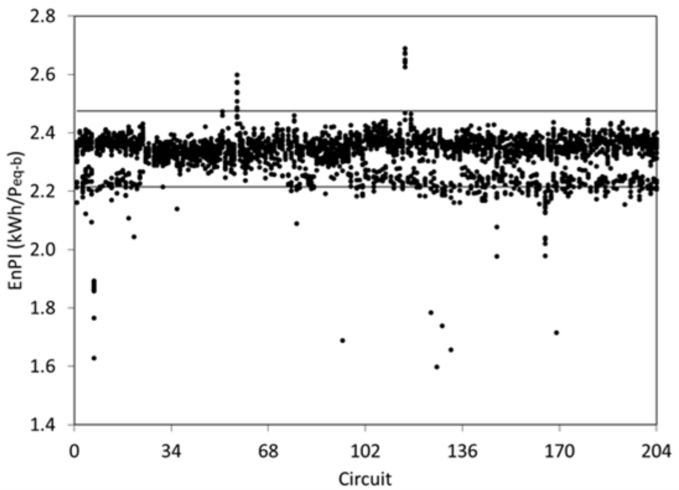

Fig. 3.Results of the outliers identification process.

Figure 4 shows that, as expected, the electricity consumed in the formation of each batch of batteries is proportional (correlation: R^2=0.99) to the number of equivalent batteries.

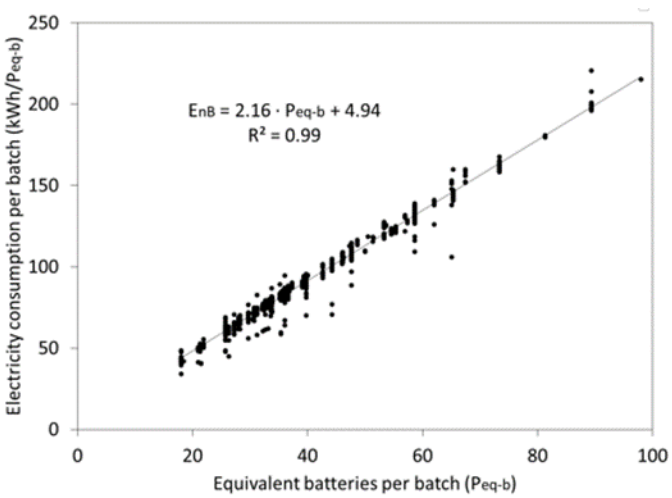

Fig. 4.Linear regression analysis: Electricity consumption per batch vs. Equivalent batteries per batch.

5.2. 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.).

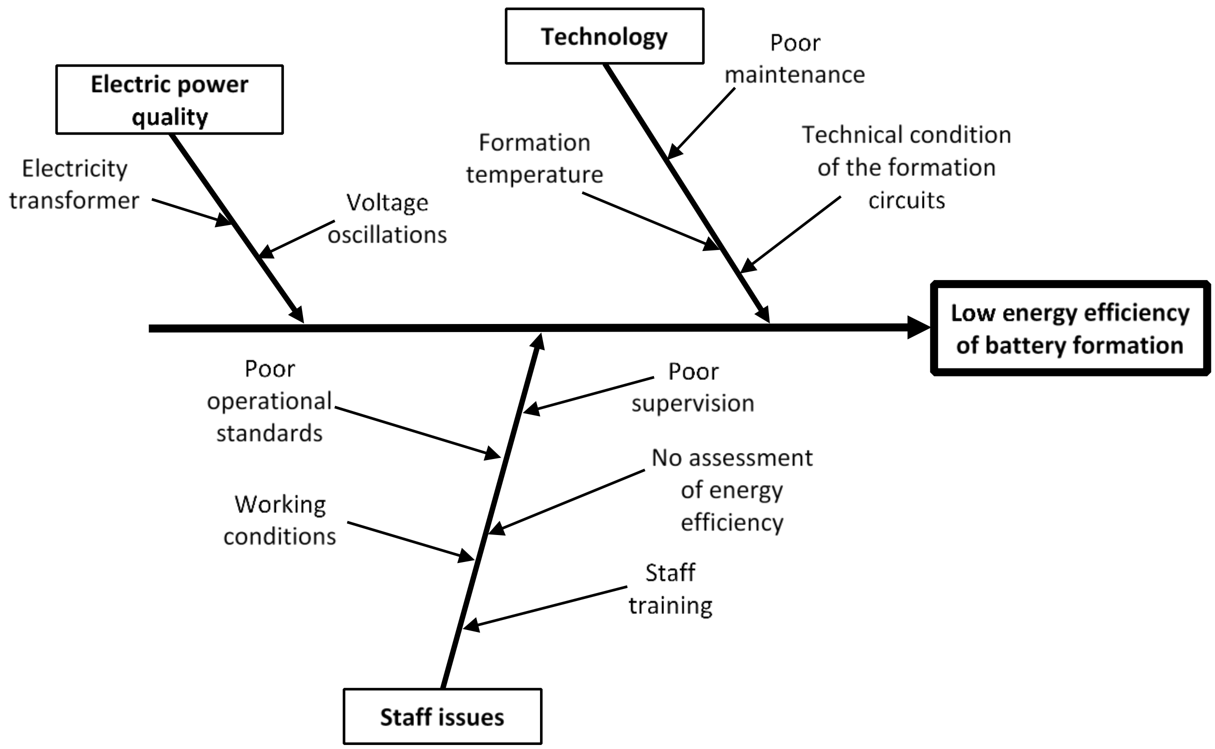

Fig. 5. Parameters affecting the energy efficiency of the battery formation process.

5.3 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 was 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 circuits to identify the factors causing the differences was carried out for each circuit.

5.4. Influence of the operational staff on the EnPI.

The formation section operates 24/7 with five teams of operational staff working in 12 h shifts (two teams per day) and 36 hours a week. The 12 hours shifts are organized starting at 5 am and at 5 pm, respectively.

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.

The main parameters affecting battery formation are the duration of the process, which affects the fatigue of the staff, and the supervisor, who influences the operational practices of the operational 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 one 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:

- 5 am to 11 am
- 11 am to 5 pm
- 5 pm to 11 pm
- 11 pm to 5 am

The same statistical approach used in section 5.3, 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.

5.5. Saving opportunities

The circuits identified in section 5.3, 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. **Error! Reference source not found.** 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 figure 6). Therefore, wires and connectors in poor technical conditions increase the electrical resistance in the circuit increasing the electricity consumption of battery formation. This points 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.

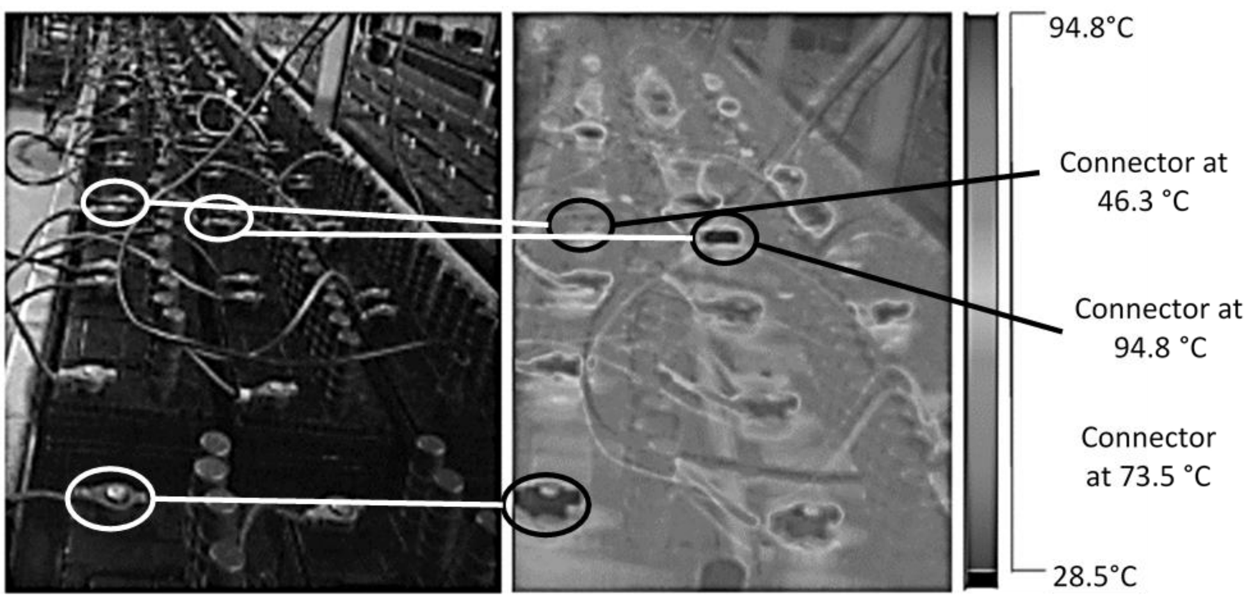

Fig. 6. Thermographic assessment of a battery batch subcircuit.

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 equation 3, the electricity consumed is directly proportional to both, the voltage (V) and the 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.

6. Energy management tools

Assessing the EnPI of the battery formation section is the first step towards the development of EM tools. Figure 7 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.

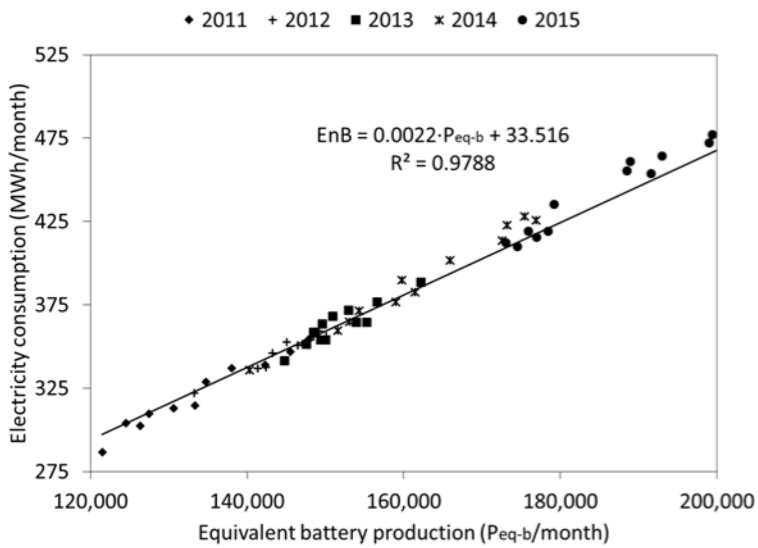

Fig. 7. Monthly EnB of the formation section.

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. On the other hand, because the formation circuits are used on a daily basis so that rapid corrective action is necessary to reduce the electricity consumption. Figure 8 shows an example of the control tools developed to assess the electricity consumption at circuit level for each batch, for two specific circuits.

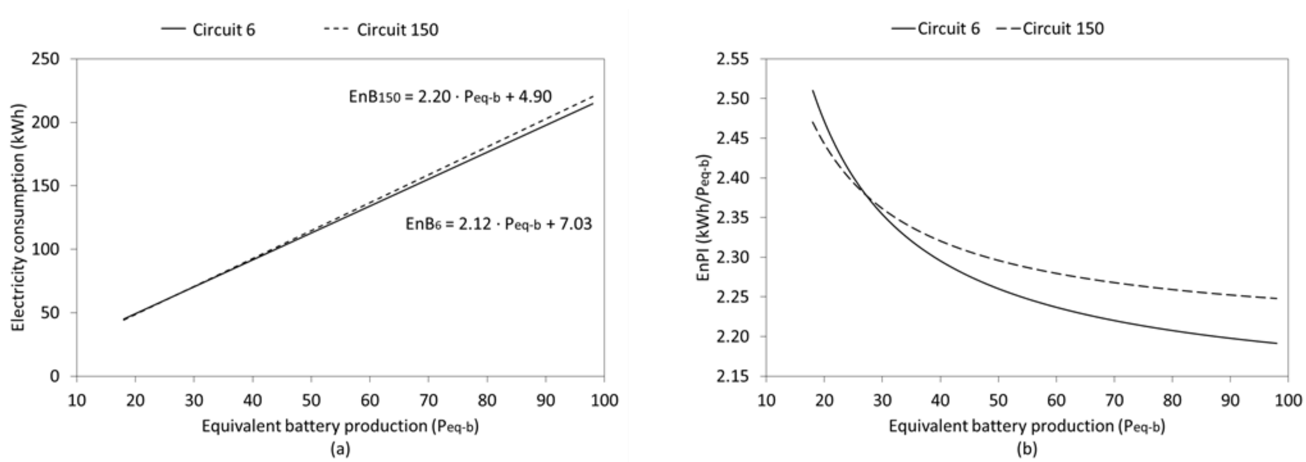

Fig. 8. Energy management tools for two formation circuits.

These tools allow rapid detection of inefficiencies at 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 figure 9)

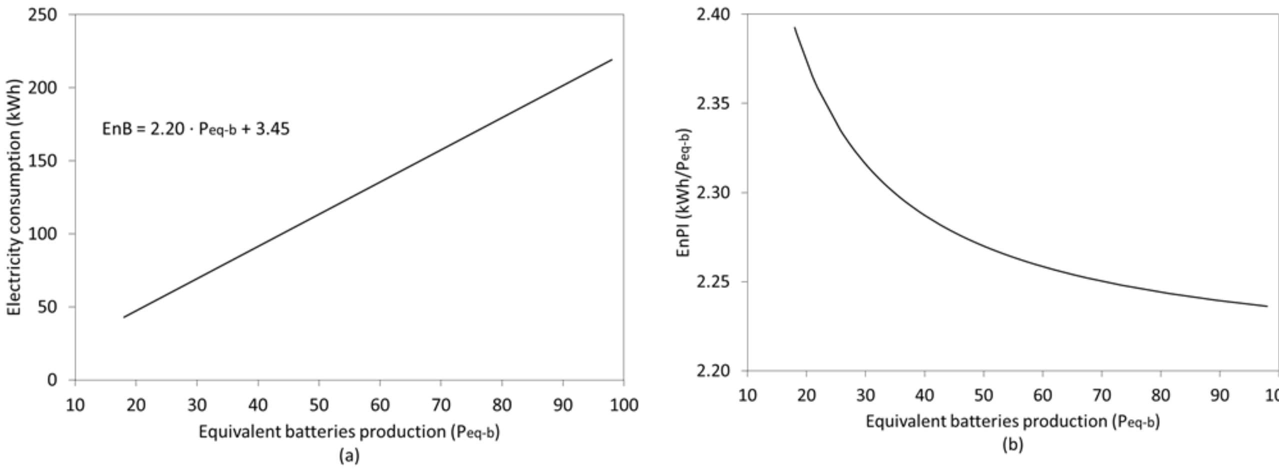

Fig. 9. Energy management tool for the operational staff teams.

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 to malpractices of the employees.

6.1. Soft sensor for 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 the formation circuits.The methodology described in section 2 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 (figure 10).

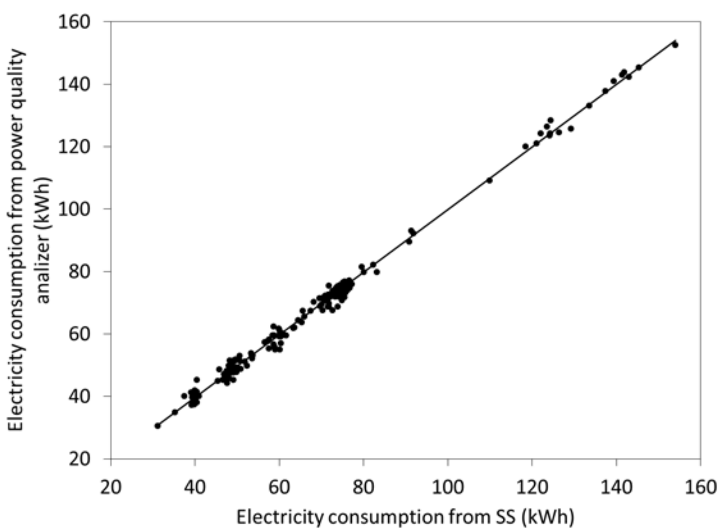

Fig. 10. Scatter plot: Power quality analyzer measures vs. SS measures.

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

7. Implementation of the EM tools

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 figure 11. The developed tools are applied at two levels: plant level and section level.

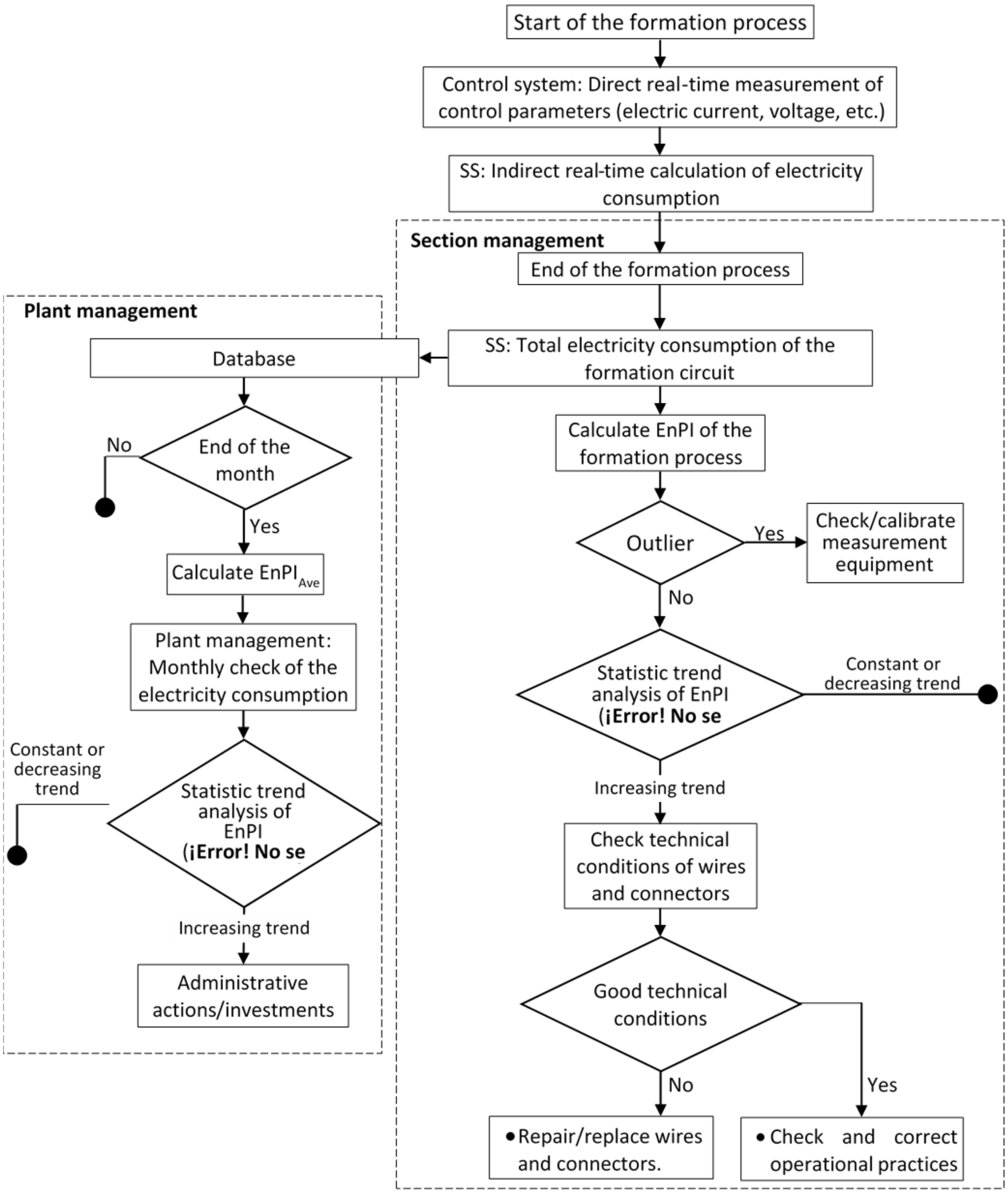

Fig. 11. EM methodology of the battery formation section.

Considering the trend analysis of the monthly average ($EnPI_{aver}$, see figure 12) 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.

Fig. 1 shows the monthly electricity consumption from 2011 to 2016. The results of implementation of the EM tools, developed in section 6, to the formation section are compared with the previous performance of the section.

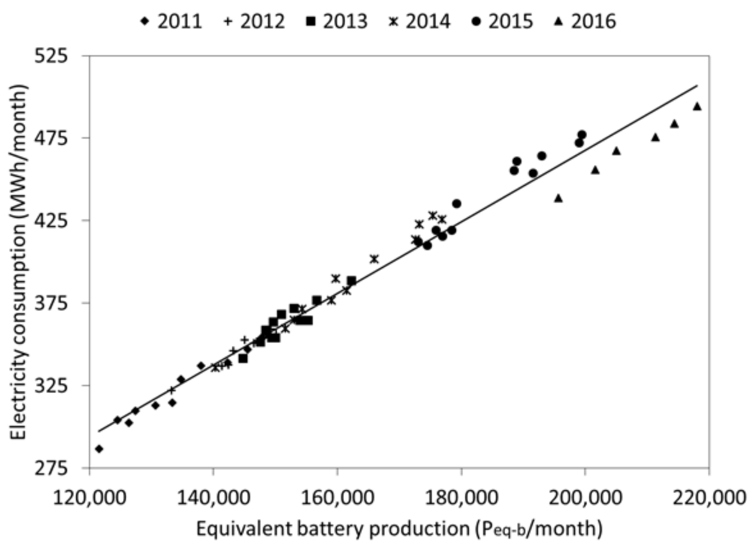

Fig. 12. Monthly electricity consumption of the battery formation section

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 1 shows the results of the implementation.

Table 1. Production parameters of the formation section during the EM tools implementation, year 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**	**2,941.9**	**2,815.8**	**126.1**	**4.3**

* EC – Electricity consumption

Comparing the electricity consumption during the implementation of the EM tools (EC: Measured) to the 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 months implementation period (with monthly reductions of 17 to 25 MWh). This shows that the EM tools improved energetic performance of battery formation, reducing the production costs. However, there are other improvement opportunities as shown in figure 13 for two of the formation circuits.

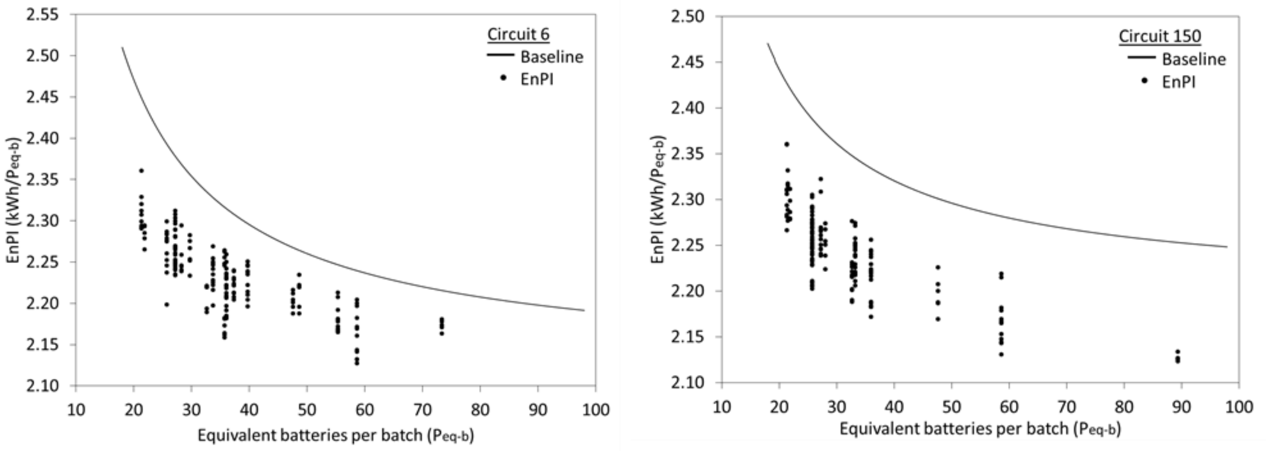

Fig. 13. EnPI of the formation batches in circuits 6 and 15 for 2016.

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 to this component.

8. 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.

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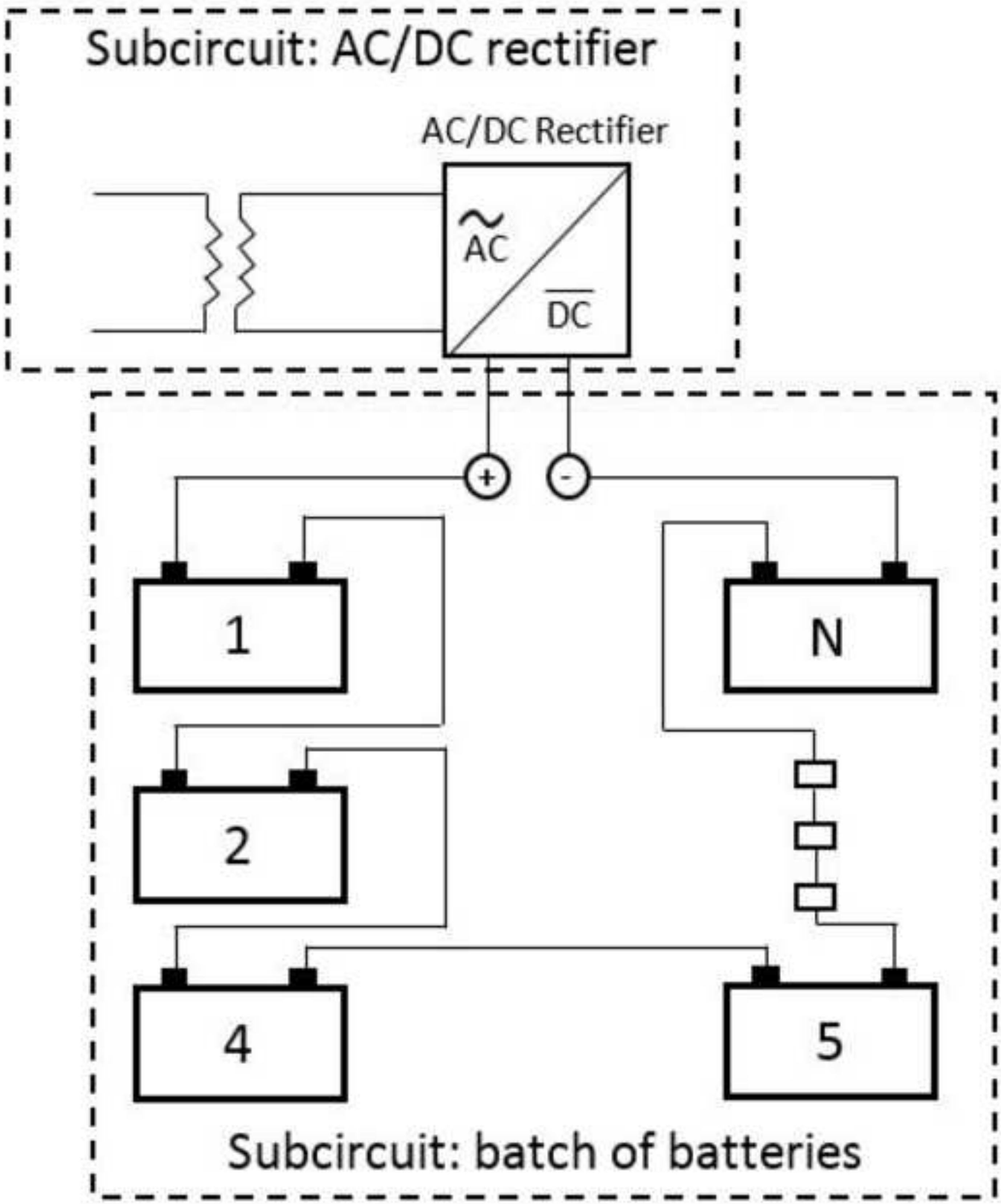
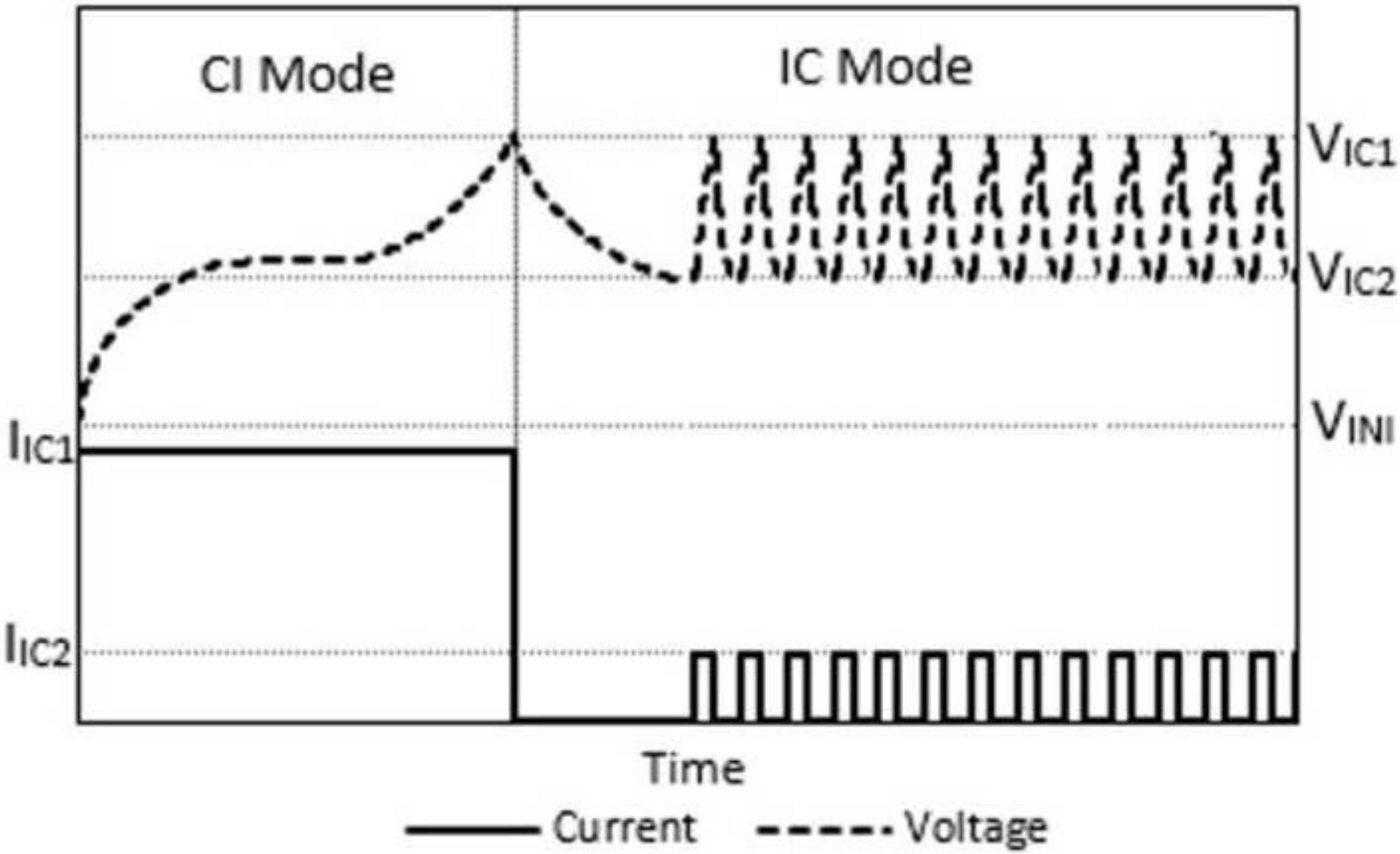

Subcircuit: AC/DC rectifier
AC/DC Rectifier
AC
DC
+
-
1
N
2
4
5
Subcircuit: batch of batteries


CI Mode
IC Mode
V_{IC1}
V_{IC2}
V_{INI}
I_{IC1}
I_{IC2}
Time
Current
Voltage

Figure

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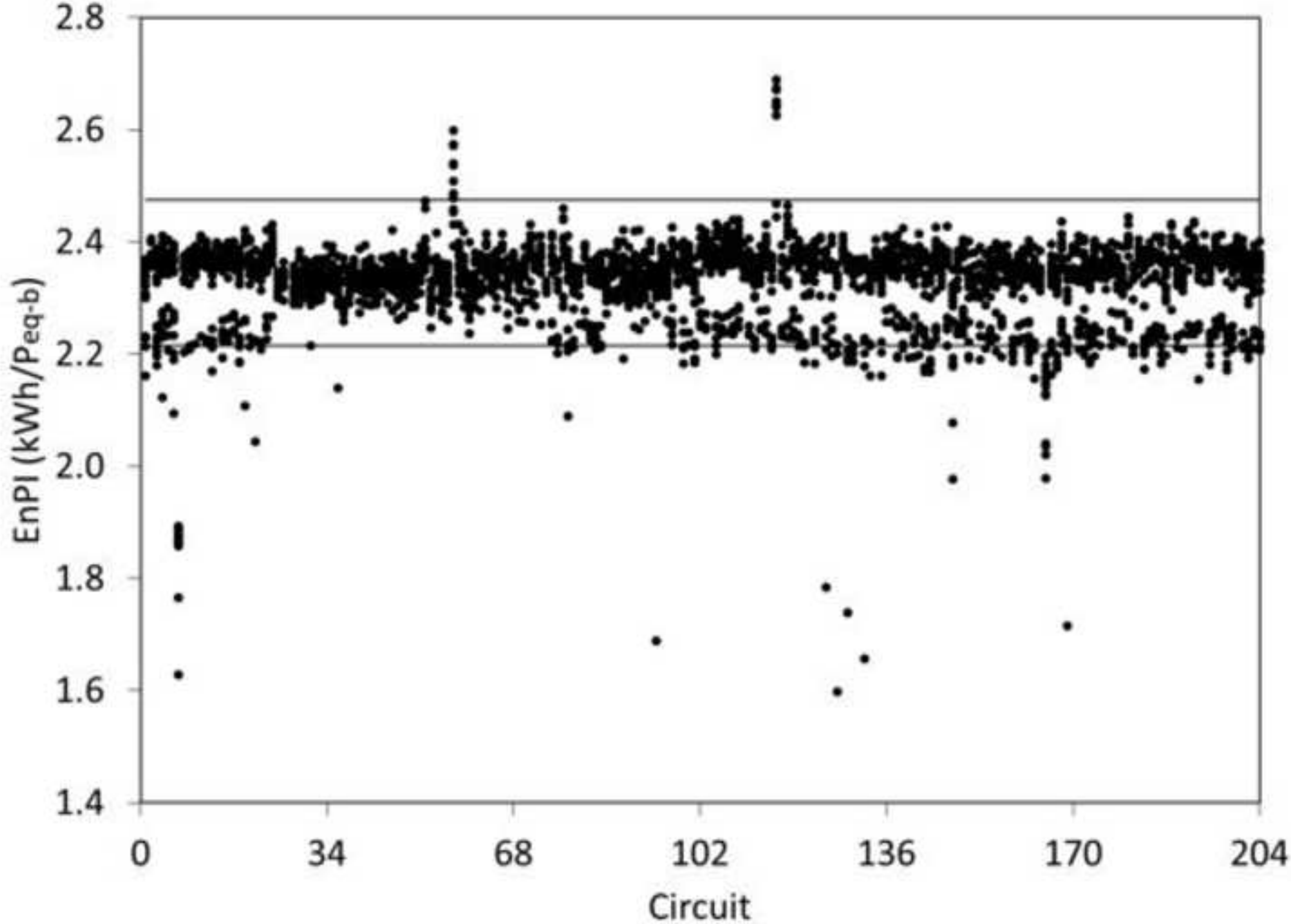

Figure

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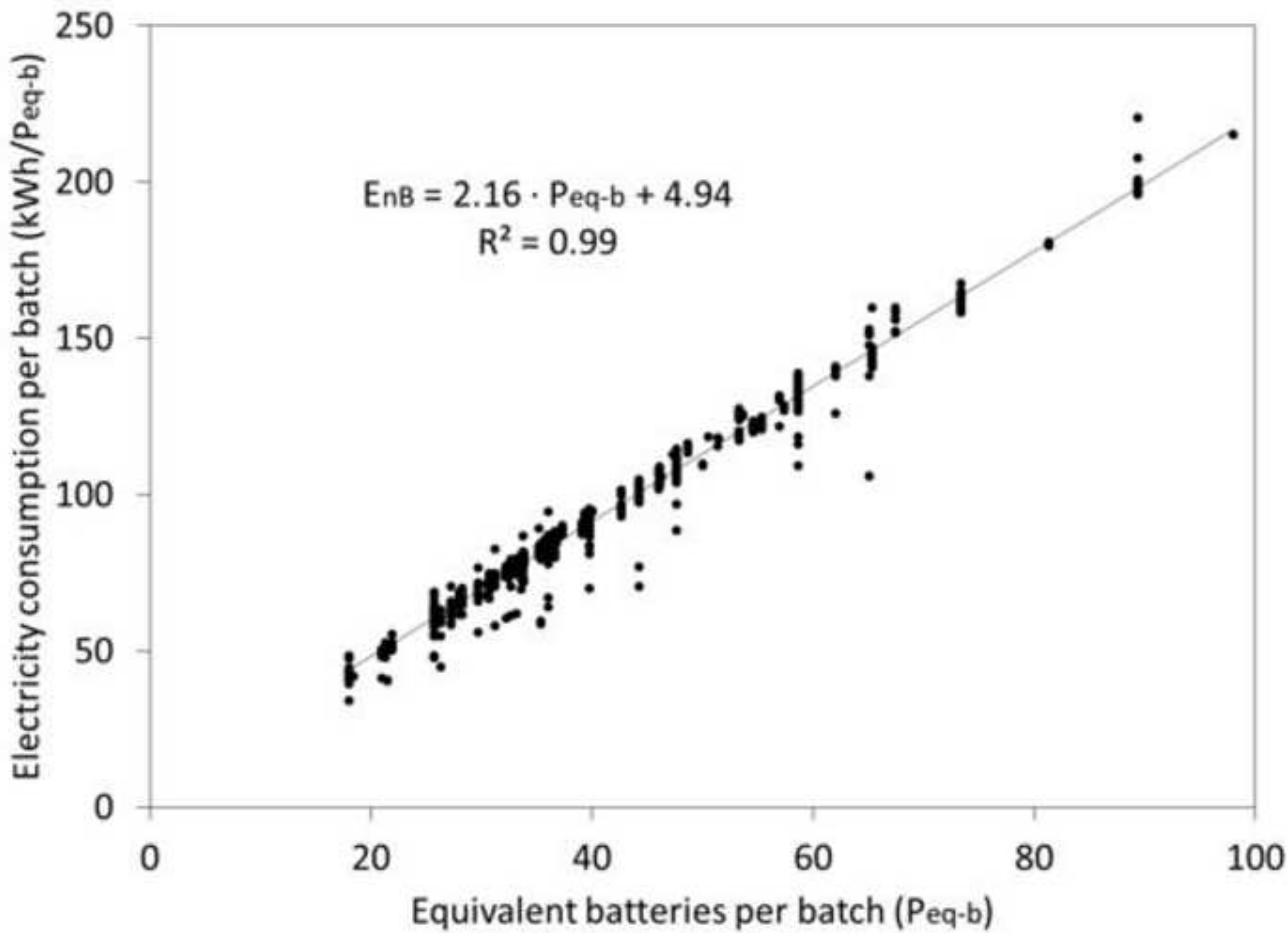

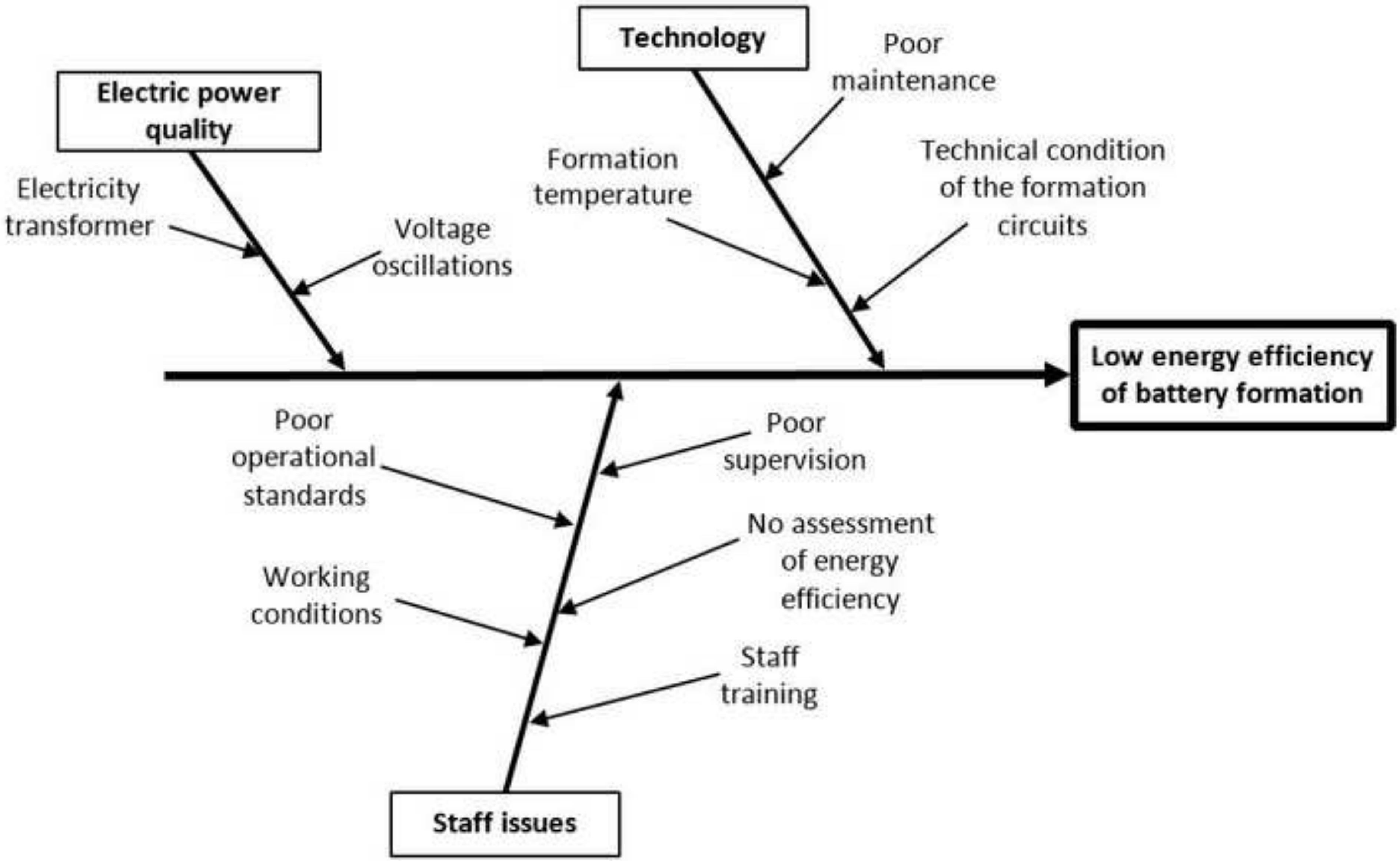
Technology
Poor maintenance
Electric power quality
Formation temperature
Technical condition of the formation circuits
Electricity transformer
Voltage oscillations
Low energy efficiency of battery formation
Poor operational standards
Poor supervision
No assessment of energy efficiency
Working conditions
Staff training
Staff issues

Figure

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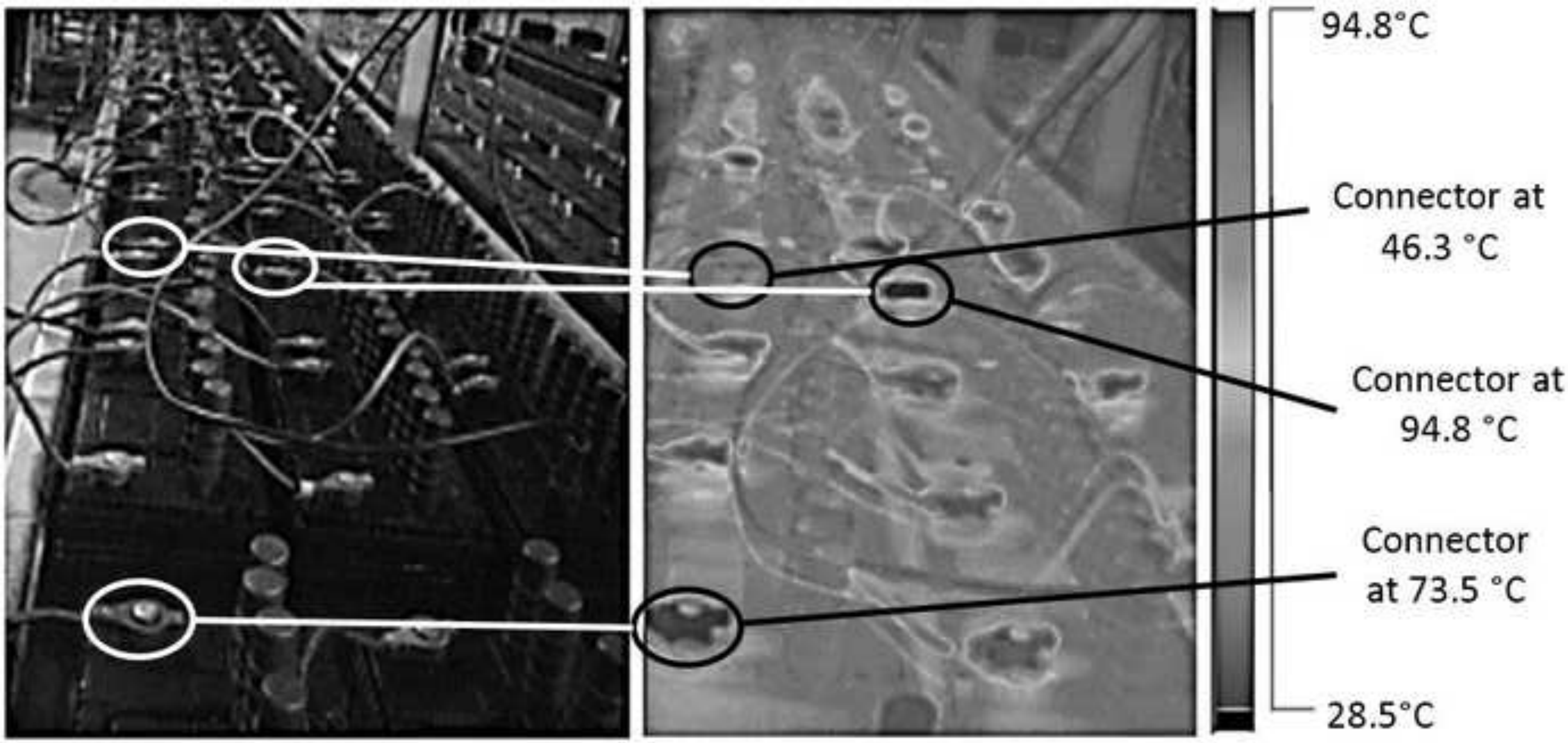

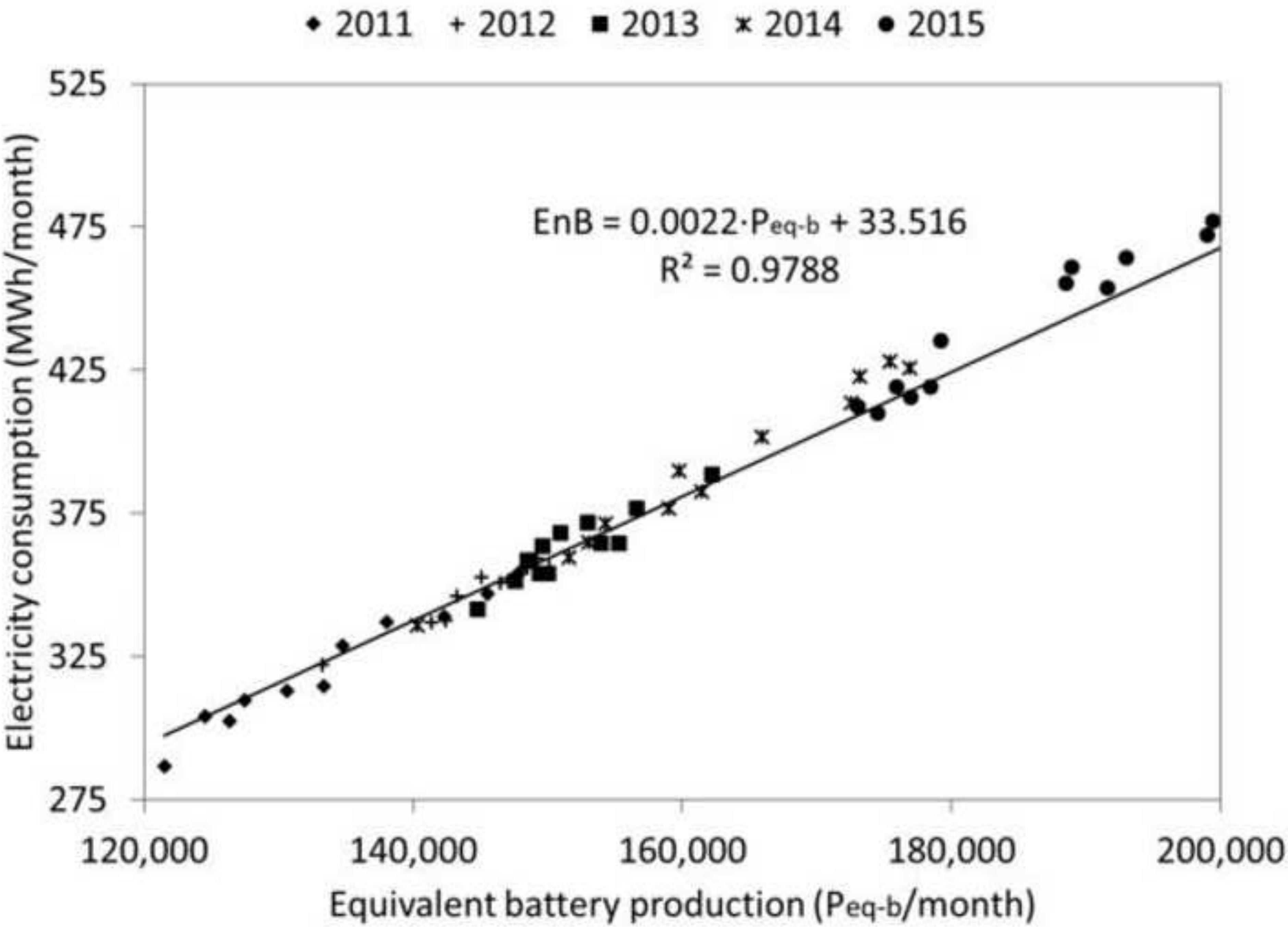
2011 2012 2013 2014 2015
EnB = 0.0022·Peq-b + 33.516
R² = 0.9788
525
475
425
375
325
275
120,000
140,000
160,000
180,000
200,000
Electricity consumption (MWh/month)
Equivalent battery production (Peq-b/month)

Figure

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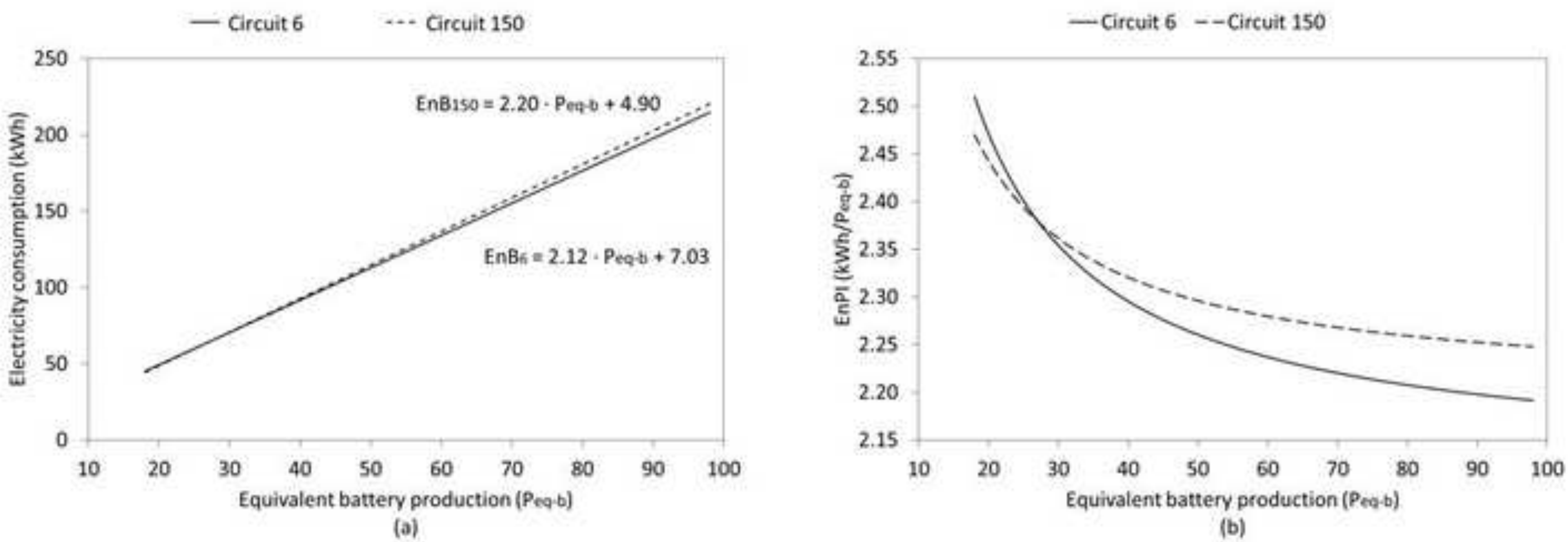
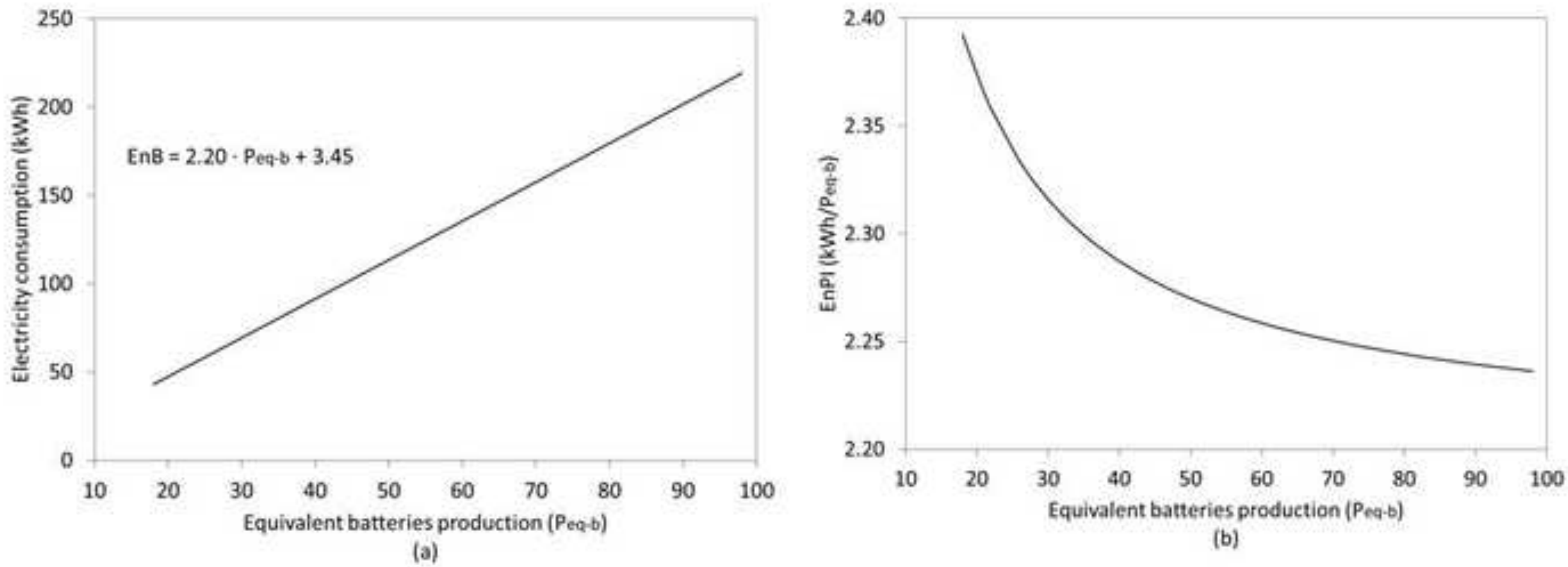
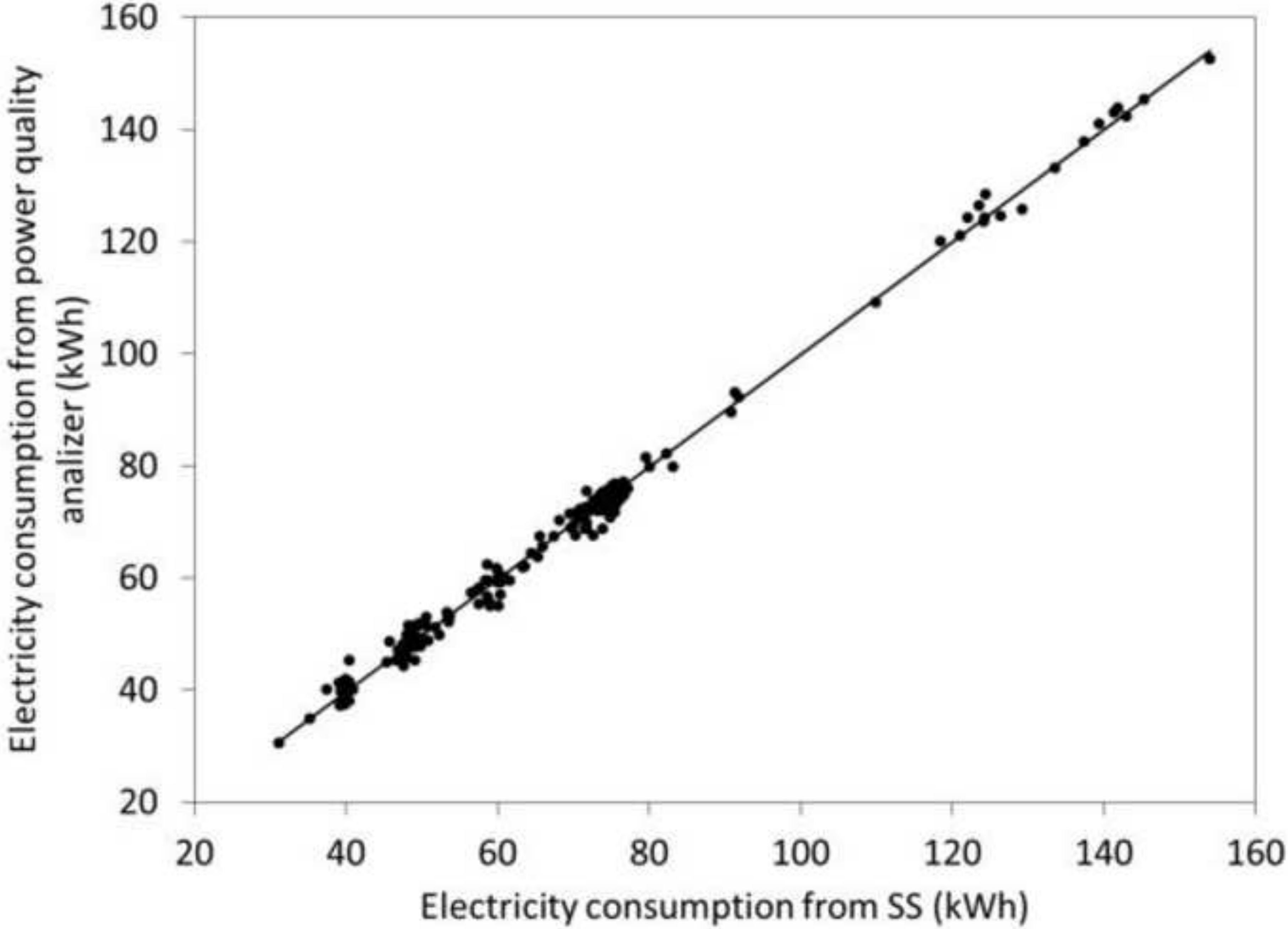


Figure

Click here to download Figure Figure 9.JPG




Electricity consumption from power quality analizer (kWh)
Electricity consumption from SS (kWh)
20
40
60
80
100
120
140
160

Figure

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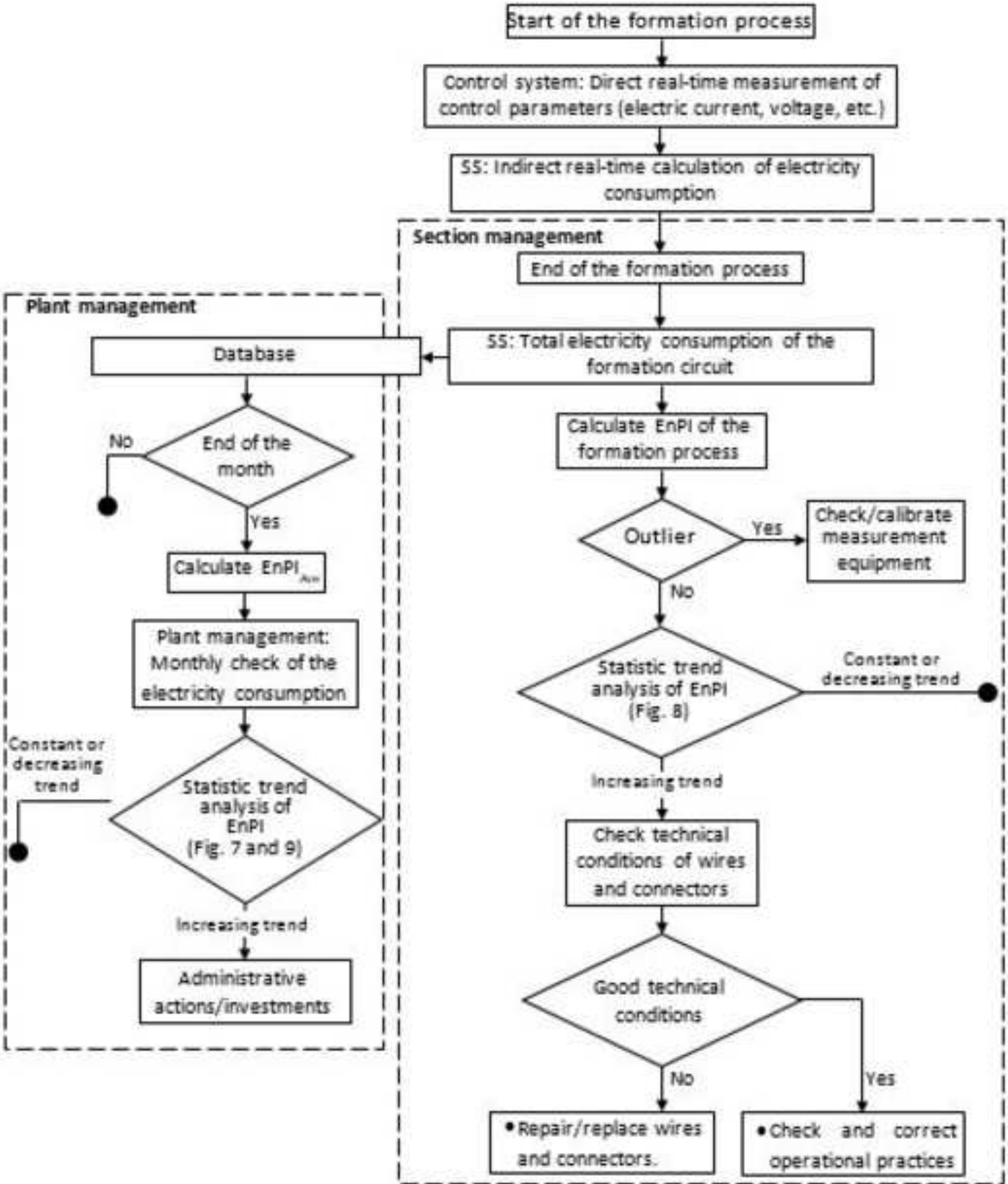
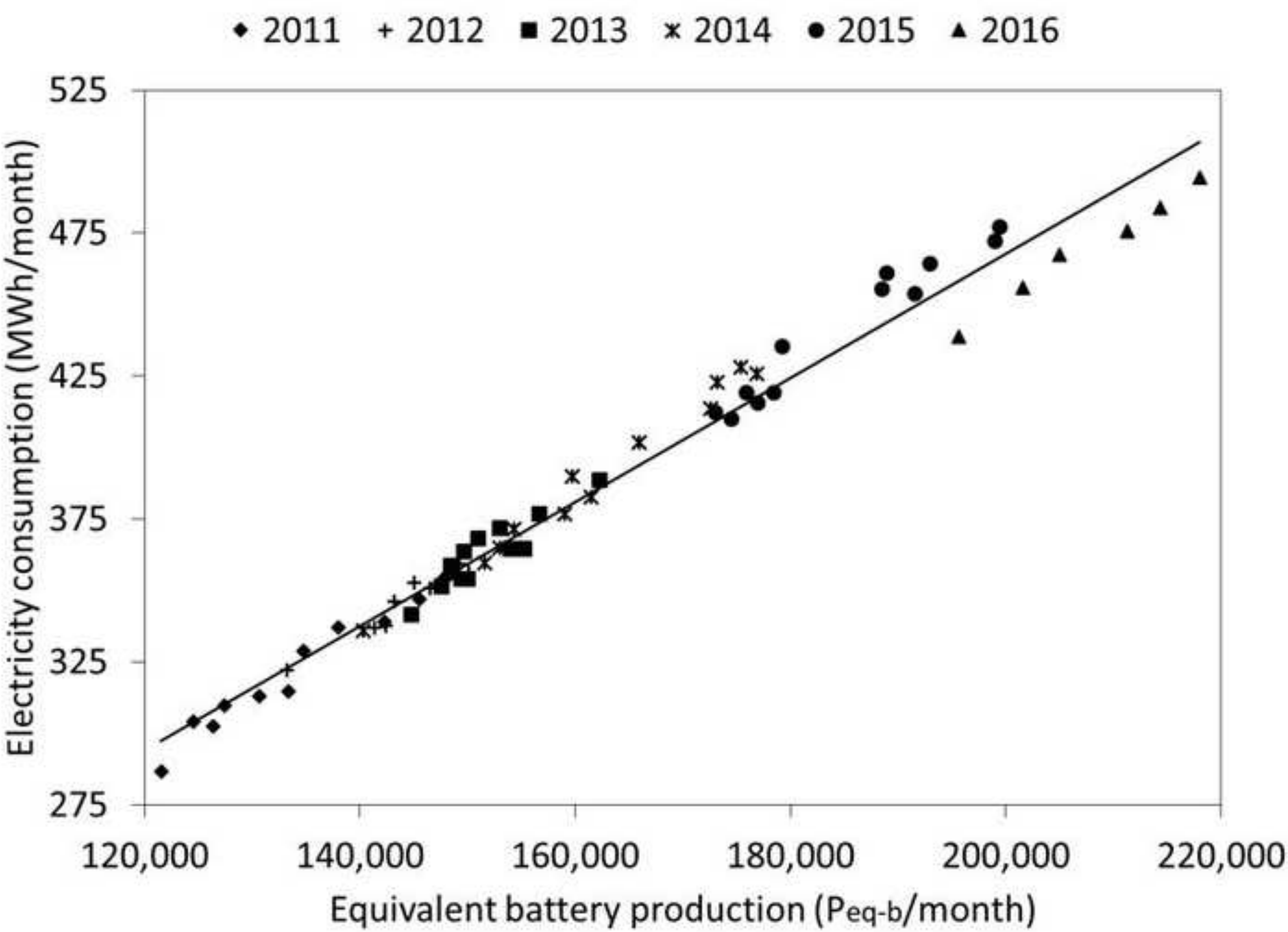


Figure Click here to download Figure Figure 12.JPG



Figure

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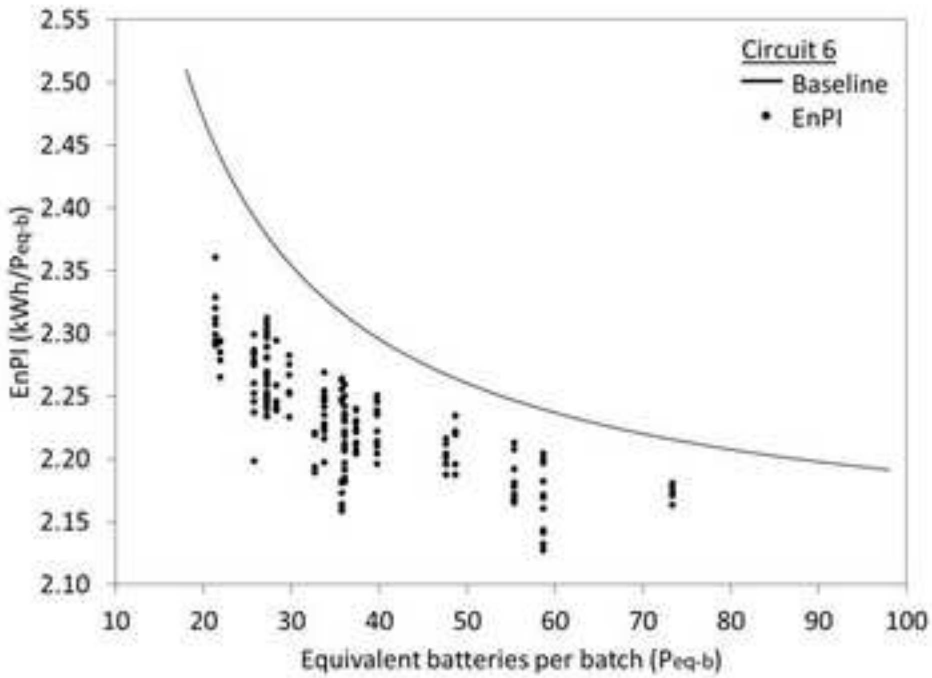

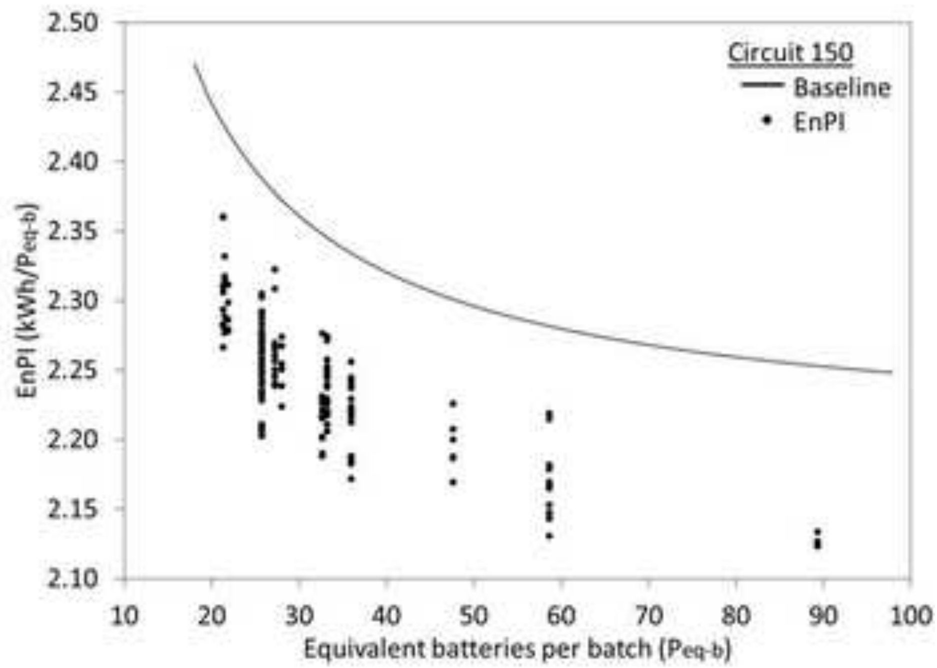

Table

Month	Battery Production	$P_{eq\text{-}b}$	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**	**2,941.9**	**2,815.8**	**126.1**	**4.3**