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(54) **Title:** METHOD AND SYSTEM FOR ONLINE ASSESSING STATE OF HEALTH OF A BATTERY

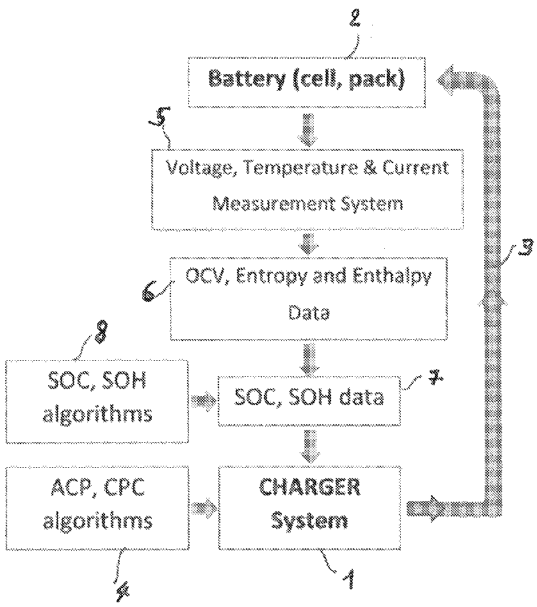

FIG.1

(57) Abstract: A method for online assessing a state of health (SOH) of an electrochemical cell, comprises a step for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said cell, said thermodynamics data including entropy and enthalpy variations ΔS, ΔH within said cell. A system for fast-charging a rechargeable battery with terminals connected to internal electrochemical cells, comprises a power supply connected to said rechargeable battery and arranged for applying a time-varying charging voltage to said battery terminals, a charging- control processor for controlling said power supply, and a system for online assessing a state of health (SOH) of said battery, said SOH assessment system comprising means for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said battery.

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"Method and system for online assessing state of health of a battery"

The present patent application claims the priority of Singapore patent application n°10201710153U filed on December 7, 2017.

TECHNICAL FIELD

The invention relates to a method for online assessing state of health of a battery (SOH). It also relates to a system implementing said online SOH assessing method.

TECHNICAL BACKGROUND

Over the last decades Energy Storage Systems (ESS) surrounded us. We are at their contact every day. With smartphones, laptops and others embedded systems hundreds of millions of lithium-ion batteries are produced each year. Moreover, with the expecting growing of electric vehicles market, even more batteries will be manufactured.

With such an amount of batteries used all over the world, it is important to ensure safety and reliability of the ESS. In order to achieve those requirements, a batteries management system (BMS) has to be used. The BMS is an electronic system which manages the battery to guarantee its safe operation. It elaborates a diagnosis from measurements and provides an optimal management of the ESS.

One part of the diagnosis is to estimate the state of health (SOH). It is a very important characteristic for a cell as well as for a pack. SOH is an indicator that evaluates the ageing of a battery compared to its fresh state. Knowing the SOH is useful for predicting when the battery should be removed. And if the battery is not operating normally, it is impacted on this indicator. Moreover to be able to perform an adaptive charging, this parameter is needed. Indeed since the battery is evolving with time, at the charging process, SOH should be used to improve battery life.

Currently SOH is assessed mostly by testing a battery during charging and discharging at a certain rate. This enables discharge capacity and voltage to be determined. Then SOH can be defined as the ratio of capacity or energy of a used battery vs. the same of a fresh one. The need to fully charge and discharge a cell is not practical to assess battery SOH on real-time basis.

This parameter SOH is difficult to estimate because it cannot be directly measured. Different estimation methods have been developed. Each of them has advantages and drawbacks.

The purpose of the present invention is to overcome these drawbacks by proposing a new method for assessing SOH.

SUMMARY OF THE INVENTION

This goal is achieved with a method for online assessing a state of health (SOH) of an electrochemical cell, said method comprising a step for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said cell, said thermodynamics data including entropy and enthalpy variations ΔS, ΔH within said cell.

The SOS assessment method according to the invention can further comprise a step for identifying the reference and chemistry of the electrochemical cell, or a step for implementing a model providing relationships between entropy ΔS and the state of health (SOH) for the electrochemical cell.

In a particular embodiment of the invention, the ΔS-SOH model has been previously obtained off line from analyzing entropy data and relating said entropy data analysis to chemical characteristics of the electrochemical cell and then to the state of health (SOH) of said cell.

The ΔS-SOH model can be implemented within an entropy-revealer tool dedicated to state of health (SOH) assessment. This entropy-revealer tool can be adapted to fill and update a database on thermodynamics and/or chemistry and/or state of health (SOH).

The entropy-revealer tool can be advantageously adapted to generate machine-learning models.

In a specific version of a SOH-assessment method of the invention, implemented for a not already known battery, the entropy-revealer tool is adapted to identify the type of said battery by accessing the database and machine learning models, and then to deliver an estimation of the state of health (SOH) with previously found learning models.

The off-line entropy analysis can detect particular open-circuit voltage (OCV) values where ΔS changes are more pronounced as the electrochemical cell ages.

The relationships between the entropy variations ΔS and the state of health (SOH) are established by using pattern recognition algorithms.

The step of estimating the state of health (SOH) comprises a step of estimating said state of health (SOH) from entropy variation ΔS profiles.

The step of estimating the state of health (SOH) comprises a step of estimating said state of health (SOH) from enthalpy variation ΔH profiles.

The entropy-revealer tool is adapted to estimate the state of health (SOH) of an electrochemical cell including a chemistry not yet referenced in the database.

The step of estimating the state of health (SOH) from thermodynamics data can advantageously comprise:

- measuring profiles of open-circuit voltage (OCV), ΔS and ΔH, for different battery references and chemistries,
- measuring profiles of OCV, ΔS and ΔH, for different battery states of health,
- defining which part of the profiles is the most interesting regarding identification and SOH estimation.
- finding a relationship between OCV, ΔS and ΔH profiles in one hand and battery reference or chemistry in another hand with a model.

The step of estimating the state of health (SOH) of a battery can comprise:

- measuring thermodynamics profiles,
- identifying the reference of said battery by using the entropy-revealer tool and from said measured thermodynamics profiles,
- estimating the state of health (SOH) by using said entropy-revealer tool and from said measured thermodynamics profiles.

According to another aspect of the invention, it is proposed a system for online assessing a state of health (SOH) of an electrochemical cell, said system comprising means for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said cell, said thermodynamics data including entropy and enthalpy variations ΔS, ΔH within said cell.

The SOH assessment system according to the invention can further comprise means for identifying the reference and chemistry of the electrochemical cell.

The SOH assessment system according to the invention can further comprise means for implementing a model providing relationships between entropy ΔS and the state of health (SOH) for the electrochemical cell.

The SOH assessment system according to the invention can further comprise an entropy-revealer tool implementing the ΔS-SOH model.

The SOH assessment system according to the invention can further comprise a database on thermodynamics and/or chemistry and/or state of health (SOH), said database being filled and updated by the entropy-revealer tool.

The SOH assessment system according to the invention can further implement machine-learning models generated by the entropy-revealer tool.

The SOH assessment system according to the invention can further comprise means for detecting particular open-circuit voltage (OCV) values where ΔS changes are more pronounced as the electrochemical cell ages.

The SOH assessment system according to the invention can further implement pattern recognition algorithms used for establishing the relationships between the entropy variations ΔS and the state of health (SOH).

The SOH estimation means can advantageously comprise:

- means for measuring profiles of open-circuit voltage (OCV), ΔS and ΔH, for different battery references and chemistries,
- means for measuring profiles of OCV, ΔS and ΔH, for different battery states of health,
- means for defining which part of the profiles is the most interesting regarding identification and SOH estimation.
- Means for finding a relationship between OCV, ΔS and ΔH profiles in one hand and battery reference or chemistry in another hand with a model.

The SOH estimation means can also comprise:

- means for measuring thermodynamics profiles,
- means for identifying the reference of said battery by using the entropy-revealer tool and from said measured thermodynamics profiles,
- means for estimating the state of health (SOH) by using said entropy-revealer tool and from said measured thermodynamics profiles.

According to another aspect of the invention, it is proposed a system for fast-charging a rechargeable battery with terminals connected to internal electrochemical cells, said fast-charging system comprising:

- a power supply connected to said rechargeable battery and arranged for applying a time-varying charging voltage to said battery terminals, thereby generating a charging current resulting in charging of said electrochemical cells,
- a charging-control processor for controlling said power supply,

said fast-charging system further comprising a system for online assessing a state of health (SOH) of said battery, said SOH assessment system comprising means for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said battery, said thermodynamics data including entropy and enthalpy variations ΔS, ΔH within said cell.

Battery state of health (SOH) is a key parameter as SOH controls the energy and the power performances of a battery together with it cycle and calendar life. SOH can be used to apply an adapted charging protocol. SOH gives valuable information on battery state of safety (SOS). Accurate SOH assessment is very important for performance and life prediction.

A new online method has been developed to assess battery SOH by the profile analysis of open- circuit voltage (OCV), entropy ΔS and enthalpy ΔH. A tool called "Entropy Revealer" (ER) is created and used for the purpose of SOH assessment. ER is based on a software which analyzes entropy data and relate them to a chemistry and then to SOH. The newly developed program automatically detects particular OCV values where ΔS changes are more pronounced as battery ages. A relationship between Entropy and SOH is then established by ER using pattern recognition algorithms. Then the models found can be used online for different applications such as smart and fast charging and for battery safety risk assessment.

BRIEF DESCRIPTION OF THE DRAWINGS

These and other features and advantages of the present invention will become better understood with regard to the following description, appended claims, and accompanying drawings wherein:

- **FIG.1** is a functional scheme of a fast-charging system implementing the SOH-assessment method according to the invention,

FIG.2 illustrates ΔS (OCV) profiles for ten different batteries from reference A, four of which are aged,

FIG.3 illustrates ΔS (OCV) profiles for nine different batteries from reference B, four of which are aged,

FIG.4 illustrates ΔS (OCV) profiles for nine different batteries from reference C,

FIG.5 illustrates ΔS (OCV) profiles for eight different batteries from reference D, four of which are aged,

FIG.6 illustrates ΔS (OCV) profiles for four different batteries from reference E,

FIG.7 illustrates ΔS (OCV) profiles for ten different batteries from reference F,

FIG. 8 features SOH computed from energy from four batteries of reference A, said batteries being aged until 350 cycles at 55 °C Celsius, and SOH being measured every 50 cycles,

FIG.9 is an OCV (SOC) plot at different cycles for Battery A1,

FIG.10 is a ΔS (SOC) plot for four Batteries from Reference A when fresh,

FIG.11 is a ΔS (SOC) plot for four Batteries from Reference A at 350 cycles,

FIG. 12 is a ΔH (SOC) plot for four Batteries from Reference A when fresh,

FIG.13 is a ΔH (SOC) plot for four Batteries from Reference A at 350 cycles,

FIG. 14 is a ΔS (OCV) plot for four Batteries from Reference A when fresh,

FIG.15 is a ΔS (OCV) plot for four Batteries from Reference A at 350 cycles,

FIG. 16 is a ΔH (OCV) plot for four Batteries from Reference A when fresh,

FIG.17 is a ΔH (OCV) plot for four Batteries from Reference A at 350 cycles,

FIG. 18 is a ΔS (OCV) plot for Battery A1,

FIG. 19 is a ΔH (OCV) plot for Battery A1,

FIG.20-22 represent in first row ΔS data between 3.7 and 3.9 volts at different ageing for different batteries, and in second row SOH evolution with ageing, each graph of this row corresponding to a battery,

FIG.23-24 are ΔS (SOC) profiles at different ageing for a LIB coin cell, and

FIG.25-27 illustrate SOH vs Cycle Number for a LIB coin cell.

DETAILED DESCRIPTION

Thermodynamics of batteries can be seen as “fingerprints”. Indeed thermodynamic data are directly linked to batteries microscopic structure. It can give us information about chemistry, age, state of charge. It is then possible to use thermodynamics for identification and characterization of batteries.

Digital fingerprint is a good analogy. The signature is unique for each individual, and statically this assertion is verified. The analogy can be pushed to the reference level. Indeed, it was observed that the thermodynamic profiles, especially ΔS, are different from one reference to another. It is the same for batteries with the same reference.

There is a better analogy than digital fingerprint. The digital fingerprint is invariant with human age or shape. It is of the same kind as DNA profiling. No matter what is the shape or the age of the person, DNA and digital fingerprint are not affected.

Thermodynamics profile are closer to voice or human face regarding this aspect. By looking at a face it is possible to recognize someone, to give its age, to have an idea of how well this person is. And there are several algorithms that use face characteristics from a picture to recognize someone, to determine its gender and even to estimate its age.

Same considerations can be made with the voice. Analogy can be even pushed further with batteries. Voice is the reflect of anatomic features such as size and shape of throat and mouth. Entropy of a battery is the reflect of internal microscopic structure and state of charge of anode and cathode. Voice can give us information about the gender. Entropy can give us information on the battery chemistry.

It is possible to estimate the age of a person with its voice. In the same fashion it is possible to estimate the age of a battery from its entropic profile. One can tell if a person is smoking just by hearing its voice. One can also tell if a battery was overheated or overcharged from its Entropy profile.

Various technologies are used to address the process and the storage of voice printing: pattern matching algorithms, neural networks, matrix representation, Vector Quantization, or decision trees. Same kind of techniques can be used as well to process thermodynamics fingerprint of a battery.

Entropy of a battery can be seen as their voice. We need to “listen” carefully to them to know more about them. Their “voice” can tell us who they are and how they feel.

Thermodynamic fingerprints for batteries include two components: Entropic and enthalpic fingerprints. These fingerprints are measured and processed to estimate the state of health.

With reference to Figure 1, a charger system 1 is provided for charging for charging a battery (cell, pack) 2 via an electric connection 3. The charger system 1 implements an Adaptive Control Protocol (ACP) algorithm or a Cascade Pulse Charging (CPC) algorithm 4. The battery 2 is monitored by a measurement system 6 for measuring Voltage, Temperature and Current. From these measurement, Data 6 on Entropy, Enthalpy and Open-Circuit Voltage (OCV) are calculated and then processed by means of SOC, SOH Algorithms to deliver Data 7 on State of Charge (SOC) and State of Health (SOH) of the battery 2. SOC and SOH Data 7 are processed by the charger system 1.

MAIN METHODS OF SOH ESTIMATION

According to [1], SOH methods estimation can be done with two different approaches, experimental or adaptive one.

With the experimental approach, cycling data is stored. Then previous knowledge of the operation performance of the cell or battery is used to estimate the SOH.

With the adaptive method, calculation of parameters sensitive to the cell degradation is used to estimate the SOH. Each of these approaches has advantages and drawbacks.

One experimental technique for SOH estimation is the direct measurement of internal resistance of the cell/battery [2] [3] [4] [5] [6] [7]. Indeed, these measurements evaluate the resistance degradation during the testing.

Another well-known experimental technique is the impedance measurement. To estimate it, Electrochemical Impedance Spectroscopy (EIS) is performed. This method is used for instance in [8] [9] [10] [11] [12] [13] [14] [15] [16] [17].

Indeed, since battery impedance is increasing with ageing, SOH estimation can be done through it. Moreover, the impedance at different frequency ranges gives information on different dynamics of the battery. So a lot of information can be extracted from the impedance. However, this methodology is not universal for all battery type. The cost and complexity of using it is then very high.

Another very popular experimental technic is the coulomb counting [18]. This method is indeed very simple. During charging and discharging the number of Ah is counted. This way transferred amount of Ah is tracked. Remain capacity is then known. Using voltage data, remained energy can also be computed. Even though it is very used, this methodology is not very accurate.

Concerning the adaptive method, an equivalent circuit is necessary. The goal is then to estimate parameters of the model that are linked to the SOH.

The first adaptive method that we are going to mention is the Kalman filter for the SOH estimation [19]. Several measurements are done over time to estimate the output variables that tend to be more precise. This method can be run online and is very accurate. However, the computational cost is pretty high.

Another adaptive method that can be mentioned is the extended Kalman filter [20] [21] [22]. This is the Kalman filter for nonlinear systems, which is usually the case for a battery system.

The approach that is proposed here is different. According to [23] , there is a link between thermodynamics and battery ageing.

Using the appropriate measurement device, one can calculate the Gibbs free energy, entropy and enthalpy of an electrochemical cell from the temperature dependence of the open circuit voltage (OCV). The measurement is nondestructive.

By looking at these thermodynamic properties, it is possible to quantify the effect of ageing. The ageing effect on electrochemical cell thermodynamics is also shown in [24] [25] [26] [27].

Following is shown how to calculate the thermodynamics properties of the electrochemical cell from the temperature dependence of the OCV.

By definition, the Gibbs Energy, $\Delta G = -nFU$, where n is the ionic charge, F is the Faraday constant, and U is the open circuit voltage. ΔG is equal to $\Delta H - T\,\Delta S$. By measuring the temperature dependence of U at a fixed state of charge, the entropy can be calculated from the slope and the enthalpy calculated from the absolute zero temperature intercept: $\Delta S = nF\,\partial U/\partial T$; $\Delta H = -nFU + nFT\,\partial U/\partial T$ or $\Delta H = -nFU$ when extrapolated to $T=0$.

What is proposed here is to quantitatively establish the relation between thermodynamic properties of an electrochemical cell and SOH.

EXPERIMENTAL

Table 1 lists the batteries used for the study. Cells with the same letter in the name have the same reference and energy are measured at C/10 rate.

Name	Type	Capacity (mAh)	Cathode chemistry
A1	18650	3200	$Li_{0.879}Ni_{0.769}Mn_{0.111}Co_{0.119}O_2$
A2	18650	3200	$Li_{0.879}Ni_{0.769}Mn_{0.111}Co_{0.119}O_2$
A3	18650	3200	$Li_{0.879}Ni_{0.769}Mn_{0.111}Co_{0.119}O_2$
A4	18650	3200	$Li_{0.879}Ni_{0.769}Mn_{0.111}Co_{0.119}O_2$

Table 1 . Batteries used for ageing

Thermodynamic properties measurement is then performed with the BA 2000 from KVI.

Cells are then placed in an environmental chamber at 55 °C Celsius and cycled at 1.5 C rate 50 times. They are then removed from the environmental chamber. Capacity, energy and thermodynamic properties are measured again. This process is repeated again until 350 cycles. At the end of the testing we have SOH and thermodynamic properties of the cells every 50 cycles from 0 to 350 cycles. 55 °C Celsius was chosen to accelerate the ageing process by a factor 8 compared to ambient temperature.

The SOH indicator that we are going to use to compare it with the thermodynamic properties of the cell is defined as following:

$$SOH = \frac{En_{max}}{En_{nominal}} .100\ \%$$

En_{max} is the maximum available energy and $En_{nominal}$ is the measured energy. The cell energy is computed as following:

$$En = \int U.I\ dt$$

The energy of battery is computed from discharge curve of the cell. In our case discharge is done at C/10 rate. For example for an electrical vehicle a battery is considered dead if the SOH value is below 80%.

Knowing that SOH has an effect on thermodynamic properties of the cell, the idea is to fetch thermodynamic data to quantitatively establish a relation between them, the SOH and thermodynamics data.

Thermodynamic data can be plotted in different ways, as illustrated by the plots in Figures 1-27:

- OCV (Open circuit voltage) vs SOC (State of charge)
- ΔS (SOC)
- ΔH (SOC)
- ΔS (OCV)
- ΔH (OCV)
- ΔS (ΔH)
- SOC (ΔS, ΔH)

The purpose of these plots is to show the reproducibility of the results for different cells from the same reference. It shows that for a given cell it is difficult to use OCV to determine the ageing level and subsequently the SOH. Coulomb counting to determine SOC is probably not well computed because probably of bad connections between the cells and the measurement device.

SOH ESTIMATION METHODOLOGY

Reference identification

Before estimating the SOH, a prior operation has to be carried. Indeed the relationship between Thermodynamics profiles and SOH is different from a reference to another. So the first step is to identify the battery reference.

It has been said that Thermodynamics profiles are also shaped by the battery chemistry; it is then expected to recognize a battery reference from their fingerprints.

To do so a large amount of thermodynamic profiles from different battery has been collected. The dataset has 126 ΔS profiles from 6 battery references. Following is a description of the measured profiles:

- Reference A: 38 ΔS profiles from 10 different batteries at different SOH (represented in Fig. 2)
- Reference B: 37 ΔS profiles from 9 different batteries at different SOH (represented in Fig. 3)
- Reference C : 9 ΔS profiles from 9 different batteries at fresh state (represented in Fig. 4)
- Reference D : 28 ΔS profiles from 8 different batteries at different SOH (represented in Fig. 5)
- Reference E: 4 ΔS profiles from 4 different batteries at fresh state (represented in Fig. 6)
- Reference F: 10 ΔS profiles from 10 different batteries at fresh state (represented in Fig. 7)

Once the data collected and normalized (represented in Fig. 8), pattern recognition algorithms are used to classify the profiles. Different algorithms are used 22 are tested and compared.

To evaluate the accuracy of the different algorithms a cross validation is carried. The different algorithms learn on 75 % of data and they are been asked to classify the 25% remaining.

By looking at the results at Table 2, the conclusion is that by using pattern recognition algorithms, it is possible to recognize a battery reference by its entropy profiles.

For example, SVM (Support vector machine) performs a perfect classification with the samples. Some algorithms can also provide a confidence on the classification.

Once the battery identified, it is time to estimate the SOH. Of course this step is not needed if we already know it.

SOH determination methodology diagram

This diagram explains the process in order to estimate battery SOH from thermodynamic data. The process is based on two main tasks: learning and estimating. The tool using this process is called entropy revealer.

To learn, entropy revealer has to fill and update a database as well as to generate models. This happens when thermodynamics data and information on the battery is already known , such as reference, chemistry or SOH.

- To estimate SOH from thermodynamic data, entropy revealer will first identify the battery type if not known already. This is done thanks to the database and machine learning models. Once known, SOH is estimated with previously found machine learning models.

SOH estimation

SOH estimation from ΔS

The strategy is going to be similar at the one used previously for identification. Pattern recognition algorithms will be used to estimate SOH. The model will learn and then estimate SOH.

The difference is that instead of identifying a reference, an SOH value is going to be estimated from ΔS profiles. To illustrate this, a battery reference is chosen: batteries labeled with the letter A. For a reference four batteries have been aged in the way described in the experimental section.

1.1	Tree	Last change: Complex Tree	Accuracy: 92.9%	20/20 features
1.2	Tree	Last change: Medium Tree	Accuracy: 92.9%	20/20 features
1.3	Tree	Last change: Simple Tree	Accuracy: 86.5%	20/20 features
1.4	Linear Discriminant	Last change: Linear Discriminant	Accuracy: 87.3%	20/20 features
1.5	Quadratic Discriminant	Last change: Quadratic Discriminant	Accuracy: 97.6%	20/20 features
1.6	SVM	Last change: Linear SVM	Accuracy: 96.8%	20/20 features
1.7	SVM	Last change: Quadratic SVM	Accuracy: 100.0%	20/20 features
1.8	SVM	Last change: Cubic SVM	Accuracy: 100.0%	20/20 features
1.9	SVM	Last change: Fine Gaussian SVM	Accuracy: 89.7%	20/20 features
1.10	SVM	Last change: Medium Gaussian SVM	Accuracy: 100.0%	20/20 features
1.11	SVM	Last change: Coarse Gaussian SVM	Accuracy: 87.3%	20/20 features
1.12	KNN	Last change: Fine KNN	Accuracy: 100.0%	20/20 features
1.13	KNN	Last change: Medium KNN	Accuracy: 91.3%	20/20 features
1.14	KNN	Last change: Coarse KNN	Accuracy: 30.2%	20/20 features
1.15	KNN	Last change: Cosine KNN	Accuracy: 92.9%	20/20 features
1.16	KNN	Last change: Cubic KNN	Accuracy: 92.1%	20/20 features
1.17	KNN	Last change: Weighted KNN	Accuracy: 99.2%	20/20 features
1.18	Ensemble	Last change: Boosted Trees	Accuracy: 30.2%	20/20 features
1.19	Ensemble	Last change: Bagged Trees	Accuracy: 99.2%	20/20 features
1.20	Ensemble	Last change: Subspace Discriminant	Accuracy: 98.4%	20/20 features
1.21	Ensemble	Last change: Subspace KNN	Accuracy: 100.0%	20/20 features
1.22	Ensemble	Last change: RUSBoosted Trees	Accuracy: 87.3%	20/20 features

Table 2. Comparison of different pattern recognition algorithms that identify a battery reference

First an OCV region is chosen. For this reference the range [3.7; 3.9] is considered. The reason is that the ΔS profiles vary more significantly with cycling in this area.

Therefore, to train the pattern recognition models, ΔS data in the chosen region are going to be used as input to the model. And SOH data computed from energy are considered for output.

Data used are in Table 3. Data from each battery is in one color. The goal is to link ΔS values at 3.7, 3.75, 3.8, 3.85 and 3.9 Volt to the output SOH.

So for one line of Table 3, we have to find a model that can predict SOH, the last column. This prediction should be based on the five ΔS values, the first five columns.

The model found has to work for all the lines of Table 3.

The simplest model is the multiple linear one. It can be written this way in our case:

$$\widehat{SOH} = a_1 * \Delta S(3.7) + a_2 * \Delta S(3.75) + a_3 * \Delta S(3.8) + a_4 * \Delta S(3.85) + a_5 * \Delta S(3.9) + c$$

It is then needed to find the six parameters to get the model (a_1 , a_2, a_3, a_4, a_5 and c) and validate it.

	ΔS at 3.7V J/K/mol)	ΔS at 3.75 V (J/K/mol)	ΔS at 3.8 V (J/K/mol)	ΔS at 3.85V ((J/K/mol)	ΔS at 3.9 V (J/K/mol)	SOH (%)
1	16.2512	12.0876	2.9175	3.0505	5.1176	100
2	19.6495	16.6629	9.2703	4.8147	6.5785	95.5806
3	17.0372	15.0715	8.4591	3.9121	5.476	91.7678
4	16.1039	15.848	9.9115	3.9869	5.349	89.8614
5	17.007	17.5516	9.9724	5.0274	5.1774	87.6651
6	17.0293	16.8205	11.1173	5.5732	5.11	84.687
7	17.1642	16.9583	12.6148	6.6178	5.1554	84.1361
8	17.4857	17.5343	14.312	5.3294	4.9653	82.3992
9	15.8957	13.6904	4.2626	2.9626	5.0441	100
10	20.4008	17.7164	7.2951	4.5617	6.5331	97.747
11	17.5181	15.4227	8.1059	3.6829	5.4391	92.8943
12	16.0911	15.773	9.2852	5.0771	5.406	91.5078

13	16.8859	16.4492	10.3556	5.404	5.612	89.5123
14	17.3915	16.7929	12.1482	5.1064	5.2267	88.5441
15	17.2416	16.9324	12.5677	6.721	5.3049	86.5905
16	17.8504	17.6292	13.6603	7.4829	5.17	84.7103
17	16.2274	12.0563	3.2596	2.966	4.9968	100
18	20.0402	18.2706	9.6853	4.8683	6.7784	96.1938
19	17.0678	15.9125	8.9438	3.7977	5.5263	91.263
20	16.174	16.793	10.3973	5.0481	5.0702	88.7543
21	17.1127	17.2736	12.4167	5.7159	5.1969	83.5842
22	17.3729	17.3294	14.0527	7.624	4.9263	83.8154
23	17.44	17.3174	14.4978	7.9727	5.006	81.7131
24	15.9723	13.1636	4.3035	2.8873	4.9644	100
25	19.8993	18.9157	9.3795	4.6881	6.5399	96.3351
26	17.0725	15.6108	7.773	3.7137	5.216	92.1466
27	15.9847	16.014	8.8332	4.3633	4.955	90.2269
28	16.7177	16.0324	11.516	4.5625	4.8224	88.0199
29	16.6957	16.5542	12.4441	4.6874	4.8302	87.1979
30	16.8383	17.0038	14.1708	5.4787	4.5672	85.228
31	17.2307	17.4241	14.9859	6.0525	4.8805	82.7027

Table 3. ΔS values at five OCV and the corresponding SOH

To validate the model a cross-validation is computed. Data are spitted in four sets. Then the pattern recognition algorithm learns with 75 % of data and test the resulting model on the remaining 25% of the data.

The parameters found are:

a1	a2	a3	a4	a5	c
0.8593	0.1299	-1.5315	-0.5339	0.4448	89.1968

A prediction can then be done. Line 15, for instance, of table 3 is considered. Parameters found and ΔS values will be used to estimate SOH:

$$\widehat{SOH} = 0.8593 * 17.24 + 0.1299 * 16.93 - 1.5315 * 12.57 - 0.5339 * 6.72 + 0.4448 * 5.30 + 89.2$$

$$\widehat{SOH} = 85.7\ \%$$

The real value is **86.6 %.** The error in SOH is less than 1 % for this estimation.

Same can be done with line 18, which correspond to another battery and another ageing:

$$\widehat{SOH} = 0.8593 * 20.04 + 0.1299 * 18.27 - 1.5315 * 9.68 - 0.5339 * 4.87 + 0.4448 * 6.78 + 89.2$$

$$\widehat{SOH} = 94.4\ \%$$

The real value is **96.2** %. The model is still good enough, the difference is 1.8 %.

When considering multiple linear regressions, results are displayed in Fig. 20. The graphs in the first row represent input data: ΔS (OCV) profiles for the four batteries in the [3.7; 3.9] OCV range.

The graphs in the second row represent the real measured SOH of the four batteries. The estimated ones by multiple linear regressions and cross validation are also represented.

The maximum error on the SOH estimation is 3.77 % and the average error is 1.57 %. It is then reasonable to consider that by using ΔS profiles and machine learning tools, one can estimate SOH with good accuracy in a robust way.

To reinforce this idea, Gaussian process regression is also tested. It gives another model with a different relationship between ΔS and SOH, but the principle is the same. It is a more complex model. Results are represented in Fig. 21.

The maximum error 3.08 % and the average error is 1.33%. This model gives even better accuracy, however the complexity is increased.

SOH estimation from ΔH

So far, only entropy variation profiles have been used. However it is also possible to estimate SOH from enthalpy variation profiles.

Same as for ΔS has been done for ΔH in the same OCV region. Findings are that higher complex model is needed to estimate SOH compared to ΔS.

Multiple linear regressions don't work well, so results are not presented here.

Gaussian process regression performs good results. According to Fig. 22 the maximum error is 3.46 % and the average error is 1.48%. Results which are comparable to SOH estimated from ΔS with Gaussian process regression.

SOH estimation for another chemistry

To reinforce the idea of universality of the methodology, this latter has been applied to another dataset. Cycling data of a 44 mAh Lib coin cell is available until 1000 cycles. The cell was cycled at C/2 rate at ambient temperature. Thermodynamic data and Energy are measured every 100 cycles.

This time ΔS (SOC) is considered instead of ΔS (OCV) to show that both can be used. At Fig. 23, ΔS (SOC) profiles are plotted at different ageing. The region [65%; 90%] SOC is chosen because the profiles evolves more in this area. Data plotted in Fig. 24 are then used as input to find the model. To be more accurate, sixΔS values are used: the ones at 65, 70, 75, 80, 85 and 90% SOC.

Fig.25 shows the evolution of SOH with cycling; they are the output data used to find the model. As previously, multiple linear regression and Gaussian process regression are tested to find a model.

Multiple linear regression give a good estimation. The max error is 3.4 % and the mean error is 2.2 %. The estimated and measures SOH are plotted on Figs. 26 and 27.

For the Gaussian process regression a max error of 0.5 % is found. The mean error is 0.2 %. This model is very accurate. It is demonstrated here that even with another battery composition, the methodology developed is applicable to estimate SOH accurately.

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CLAIMS

1. A method for online assessing a state of health (SOH) of an electrochemical cell, said method comprising a step for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said cell, said thermodynamics data including entropy and enthalpy variations ΔS, ΔH within said cell.

2. The method of Claim 1, further comprising a step for identifying the reference and chemistry of the electrochemical cell.

3. The method of Claim 1, further comprising a step for implementing a model providing relationships between entropy ΔS and the state of health (SOH) for the electrochemical cell.

4. The method of Claim 3, wherein the ΔS-SOH model has been previously obtained off line from analyzing entropy data and relating said entropy data analysis to chemical characteristics of the electrochemical cell and then to the state of health (SOH) of said cell.

5. The method of Claim 4, wherein the ΔS-SOH model is implemented within an entropy-revealer tool dedicated to state of health (SOH) assessment.

6. The method of Claim 6, wherein the entropy-revealer tool is adapted to fill and update a database on thermodynamics and/or chemistry and/or state of health (SOH).

7. The method of Claim 5 or 6, wherein the entropy-revealer tool is adapted to generate machine-learning models.

8. The method of Claim 7, implemented for a not already known battery, wherein the entropy-revealer tool is adapted to identify the type of said battery by accessing the database and machine learning models, and then to deliver an estimation of the state of health (SOH) with previously found learning models.

9. The method of any of Claims 4 to 8, wherein the off-line entropy analysis detects particular open-circuit voltage (OCV) values where ΔS changes are more pronounced as

the electrochemical cell ages.

10. The method of any of Claim 3 to 9, wherein the relationships between the entropy variations ΔS and the state of health (SOH) are established by using pattern recognition algorithms.

11. The method of Claim 1, wherein the step of estimating the state of health (SOH) comprises a step of estimating said state of health (SOH) from entropy variation ΔS profiles.

12. The method of Claim 1, wherein the step of estimating the state of health (SOH) comprises a step of estimating said state of health (SOH) from enthalpy variation ΔH profiles.

13. The method of Claim 1, wherein the entropy-revealer tool is adapted to estimate the state of health (SOH) of an electrochemical cell including a chemistry not yet referenced in the database.

14. The method of Claim 1, wherein the step of estimating the state of health (SOH) from thermodynamics data comprises:

- measuring profiles of open-circuit voltage (OCV), ΔS and ΔH, for different battery references and chemistries,
- measuring profiles of OCV, ΔS and ΔH, for different battery states of health,
- defining which part of the profiles is the most interesting regarding identification and SOH estimation.
- finding a relationship between OCV, ΔS and ΔH profiles in one hand and battery reference or chemistry in another hand with a model.

15. The method of Claim 14, wherein the step of estimating the state of health (SOH) of a battery comprises:

- measuring thermodynamics profiles,
- identifying the reference of said battery by using the entropy-revealer tool and from said measured thermodynamics profiles,
- estimating the state of health (SOH) by using said entropy-revealer tool and from

said measured thermodynamics profiles.

16. A system for online assessing a state of health (SOH) of an electrochemical cell, said system comprising means for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said cell, said thermodynamics data including entropy and enthalpy variations ΔS, ΔH within said cell.

17. The SOH assessment system of Claim 1, further comprising means for identifying the reference and chemistry of the electrochemical cell.

18. The SOH assessment system of Claim 16, further comprising means for implementing a model providing relationships between entropy ΔS and the state of health (SOH) for the electrochemical cell.

19. The SOH assessment system of Claim 18, further comprising an entropy-revealer tool implementing the ΔS-SOH model.

20. The SOH assessment system of Claim 19, further comprising a database on thermodynamics and/or chemistry and/or state of health (SOH), said database being filled and updated by the entropy-revealer tool.

21. The SOH assessment system of Claim 19, implementing machine-learning models generated by the entropy-revealer tool.

22. The SOH assessment system of Claim 19, further comprising means for detecting particular open-circuit voltage (OCV) values where ΔS changes are more pronounced as the electrochemical cell ages.

23. The SOH assessment system of Claim 19, implementing pattern recognition algorithms used for establishing the relationships between the entropy variations ΔS and the state of health (SOH).

24. The SOH assessment system of Claim 19, wherein the SOH estimation means comprise

- means for measuring profiles of open-circuit voltage (OCV), ΔS and ΔH, for different battery references and chemistries,

- means for measuring profiles of OCV, ΔS and ΔH, for different battery states of health,

- means for defining which part of the profiles is the most interesting regarding identification and SOH estimation.

- Means for finding a relationship between OCV, ΔS and ΔH profiles in one hand and battery reference or chemistry in another hand with a model.

25. The SOH assessment system of Claim 19, wherein the SOH estimation means comprise:

- means for measuring thermodynamics profiles,

- means for identifying the reference of said battery by using the entropy-revealer tool and from said measured thermodynamics profiles,

- means for estimating the state of health (SOH) by using said entropy-revealer tool and from said measured thermodynamics profiles.

26. A system for fast-charging a rechargeable battery with terminals connected to internal electrochemical cells, said fast-charging system comprising:

- a power supply connected to said rechargeable battery and arranged for applying a time-varying charging voltage to said battery terminals, thereby generating a charging current resulting in charging of said electrochemical cells,

- a charging-control processor for controlling said power supply,

said fast-charging system further comprising a system for online assessing a state of health (SOH) of said battery, said SOH assessment system comprising means for estimating said state of health (SOH) of said electrochemical cell from thermodynamics data related to said battery, said thermodynamics data including entropy and enthalpy variations ΔS, ΔH within said cell.

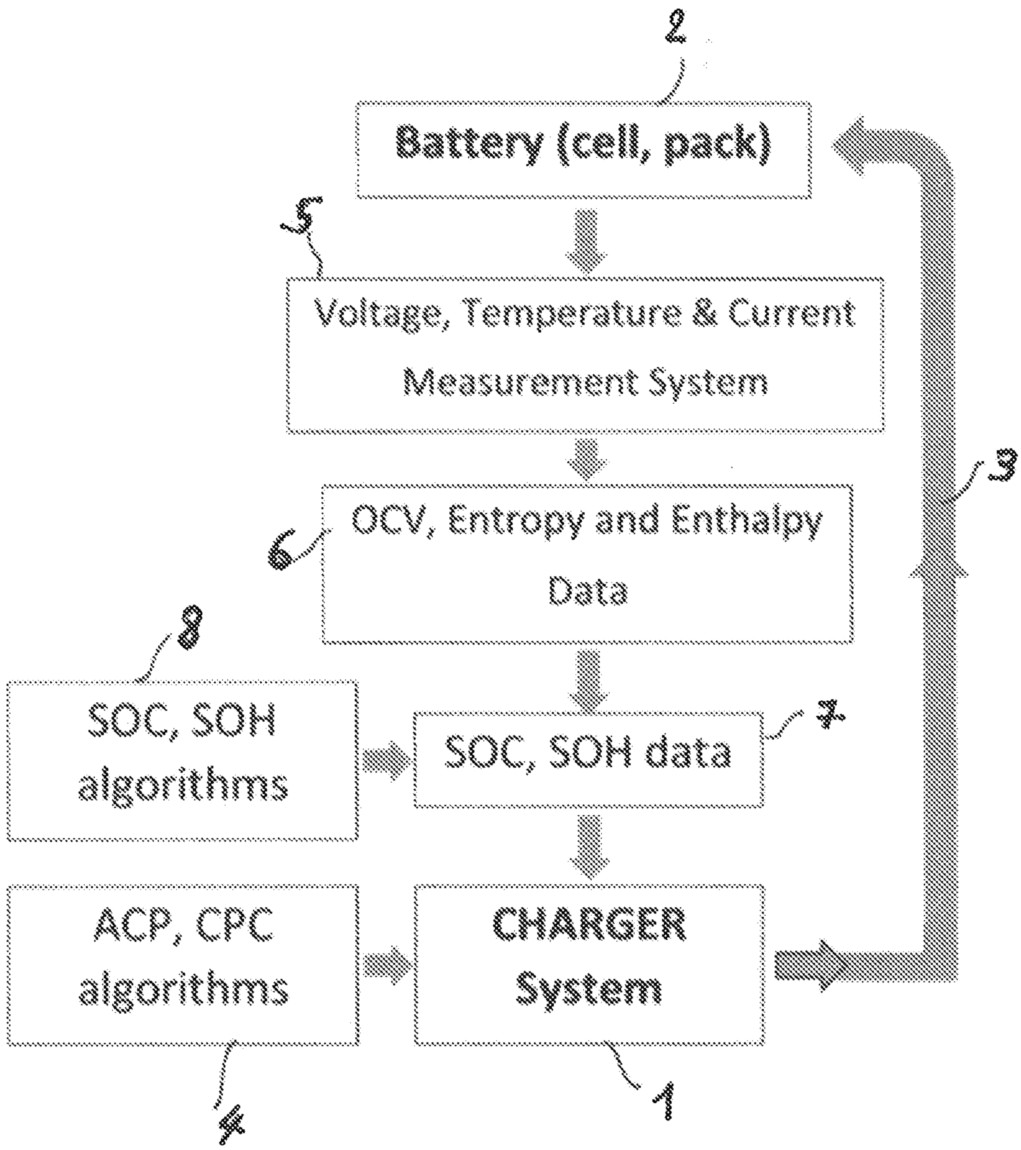
2
Battery (cell, pack)
5
Voltage, Temperature & Current
Measurement System
3
6
OCV, Entropy and Enthalpy
Data
8
SOC, SOH
algorithms
SOC, SOH data
7
ACP, CPC
algorithms
CHARGER
System
4
1

FIG.1

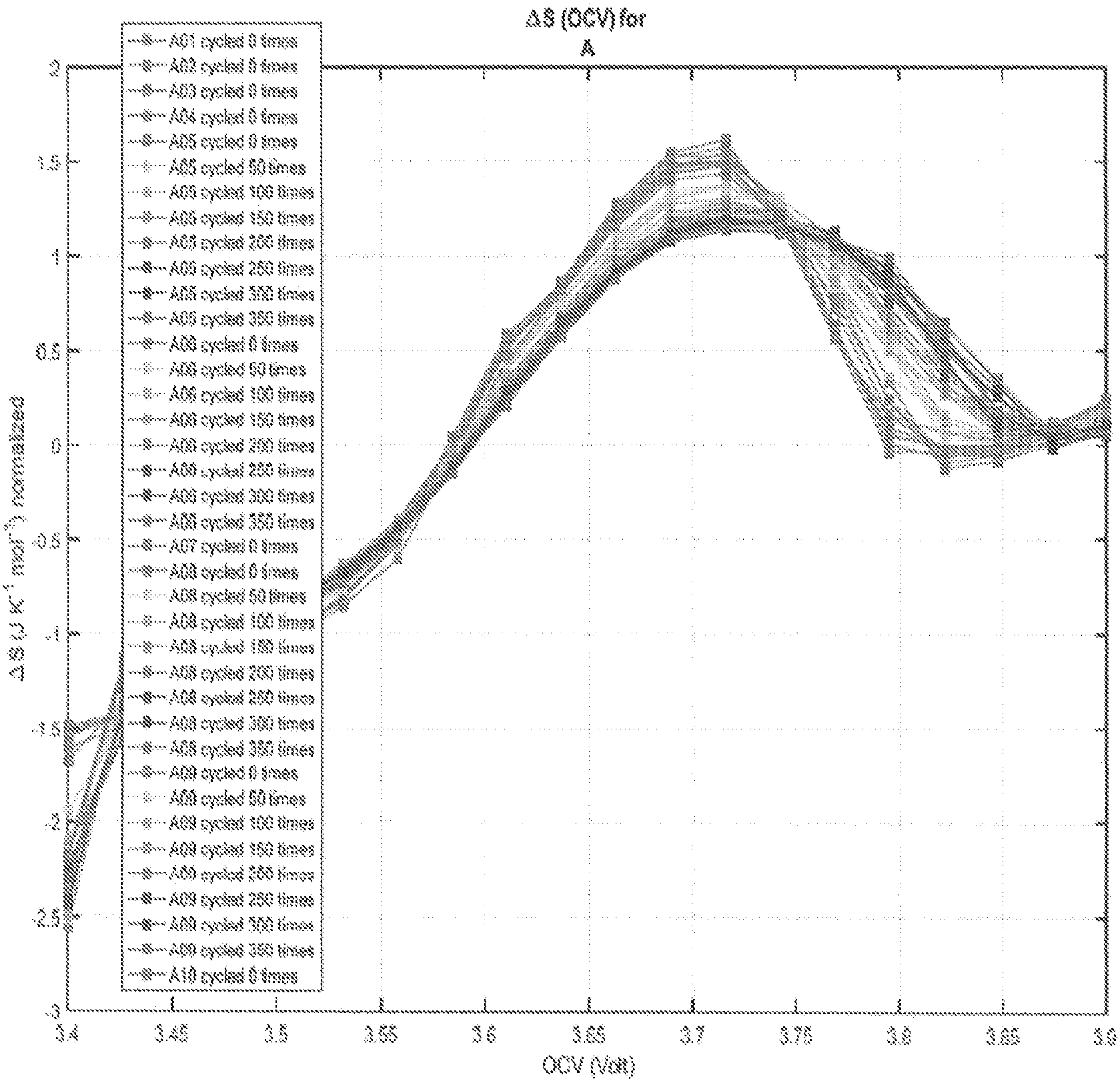
ΔS (OCV) for
A
A01 cycled 0 times
A02 cycled 0 times
A03 cycled 0 times
A04 cycled 0 times
A05 cycled 0 times
A05 cycled 50 times
A05 cycled 100 times
A05 cycled 150 times
A05 cycled 200 times
A05 cycled 250 times
A05 cycled 300 times
A05 cycled 350 times
A06 cycled 0 times
A06 cycled 50 times
A06 cycled 100 times
A06 cycled 150 times
A06 cycled 200 times
A06 cycled 250 times
A06 cycled 300 times
A06 cycled 350 times
A07 cycled 0 times
A08 cycled 0 times
A08 cycled 50 times
A08 cycled 100 times
A08 cycled 150 times
A08 cycled 200 times
A08 cycled 250 times
A08 cycled 300 times
A08 cycled 350 times
A09 cycled 0 times
A09 cycled 50 times
A09 cycled 100 times
A09 cycled 150 times
A09 cycled 200 times
A09 cycled 250 times
A09 cycled 300 times
A09 cycled 350 times
A10 cycled 0 times
ΔS (J K^-1 mol^-1) normalized
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
3.4
3.45
3.5
3.55
3.6
3.65
3.7
3.75
3.8
3.85
3.9
OCV (Volt)

FIG.2

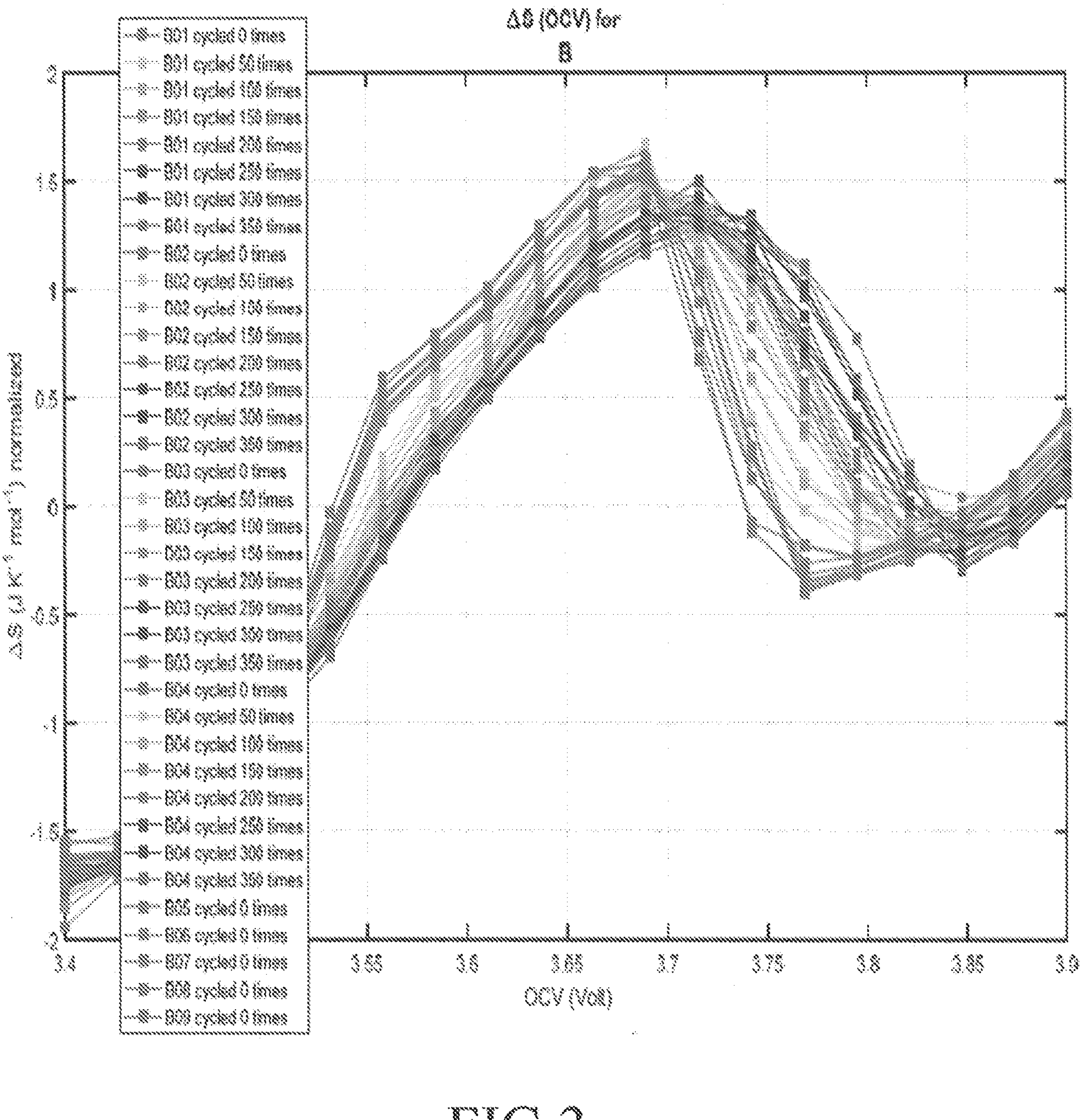
ΔS (OCV) for
B
ΔS (μ K⁻¹ mol⁻¹) normalized
OCV (Volt)
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
3.4
3.55
3.6
3.65
3.7
3.75
3.8
3.85
3.9
B01 cycled 0 times
B01 cycled 50 times
B01 cycled 100 times
B01 cycled 150 times
B01 cycled 200 times
B01 cycled 250 times
B01 cycled 300 times
B01 cycled 350 times
B02 cycled 0 times
B02 cycled 50 times
B02 cycled 100 times
B02 cycled 150 times
B02 cycled 200 times
B02 cycled 250 times
B02 cycled 300 times
B02 cycled 350 times
B03 cycled 0 times
B03 cycled 50 times
B03 cycled 100 times
B03 cycled 150 times
B03 cycled 200 times
B03 cycled 250 times
B03 cycled 300 times
B03 cycled 350 times
B04 cycled 0 times
B04 cycled 50 times
B04 cycled 100 times
B04 cycled 150 times
B04 cycled 200 times
B04 cycled 250 times
B04 cycled 300 times
B04 cycled 350 times
B05 cycled 0 times
B06 cycled 0 times
B07 cycled 0 times
B08 cycled 0 times
B09 cycled 0 times

FIG.3

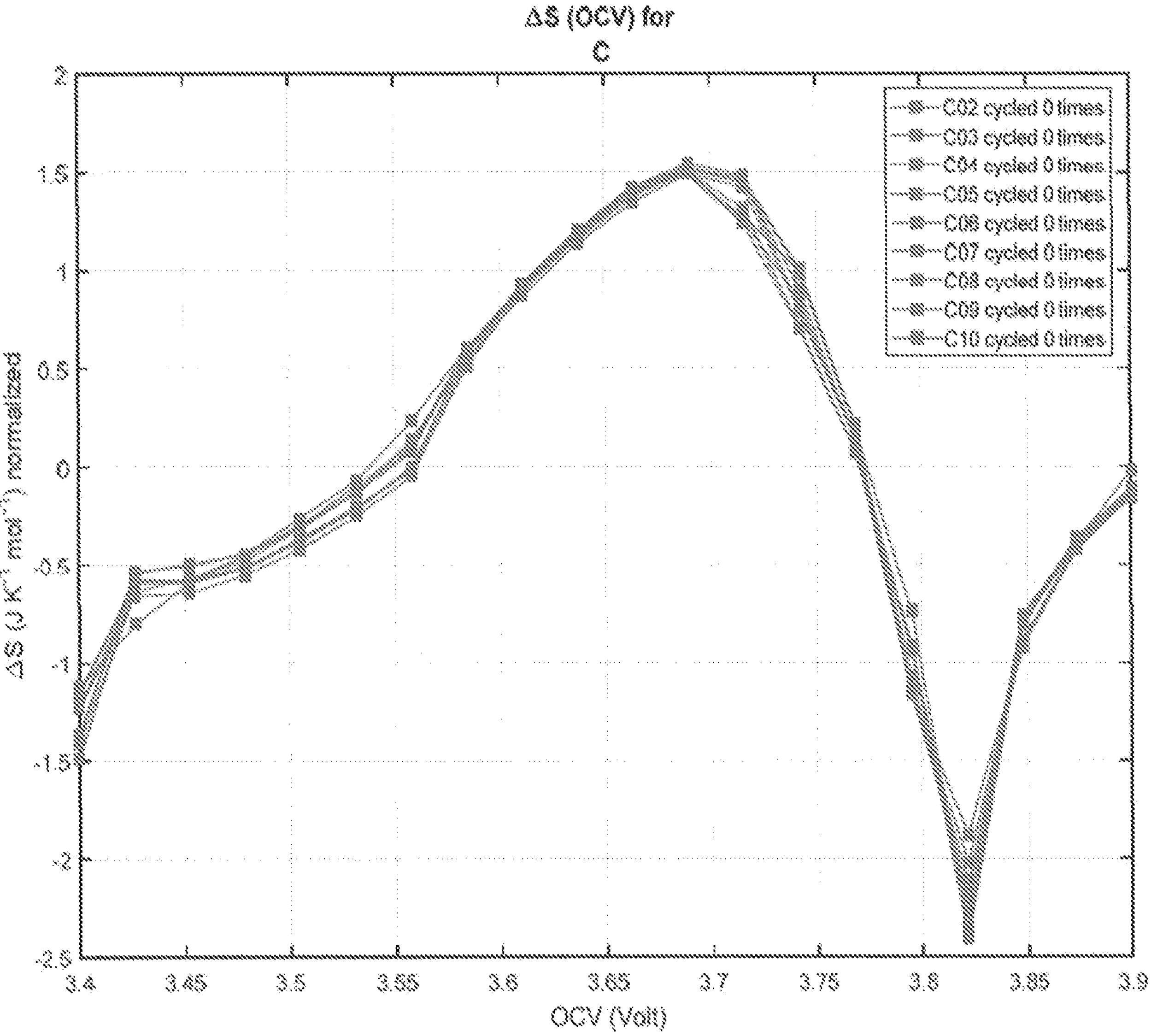
ΔS (OCV) for
C
C02 cycled 0 times
C03 cycled 0 times
C04 cycled 0 times
C05 cycled 0 times
C06 cycled 0 times
C07 cycled 0 times
C08 cycled 0 times
C09 cycled 0 times
C10 cycled 0 times
ΔS (J K⁻¹ mol⁻¹) normalized
OCV (Volt)
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
3.4
3.45
3.5
3.55
3.6
3.65
3.7
3.75
3.8
3.85
3.9

FIG.4

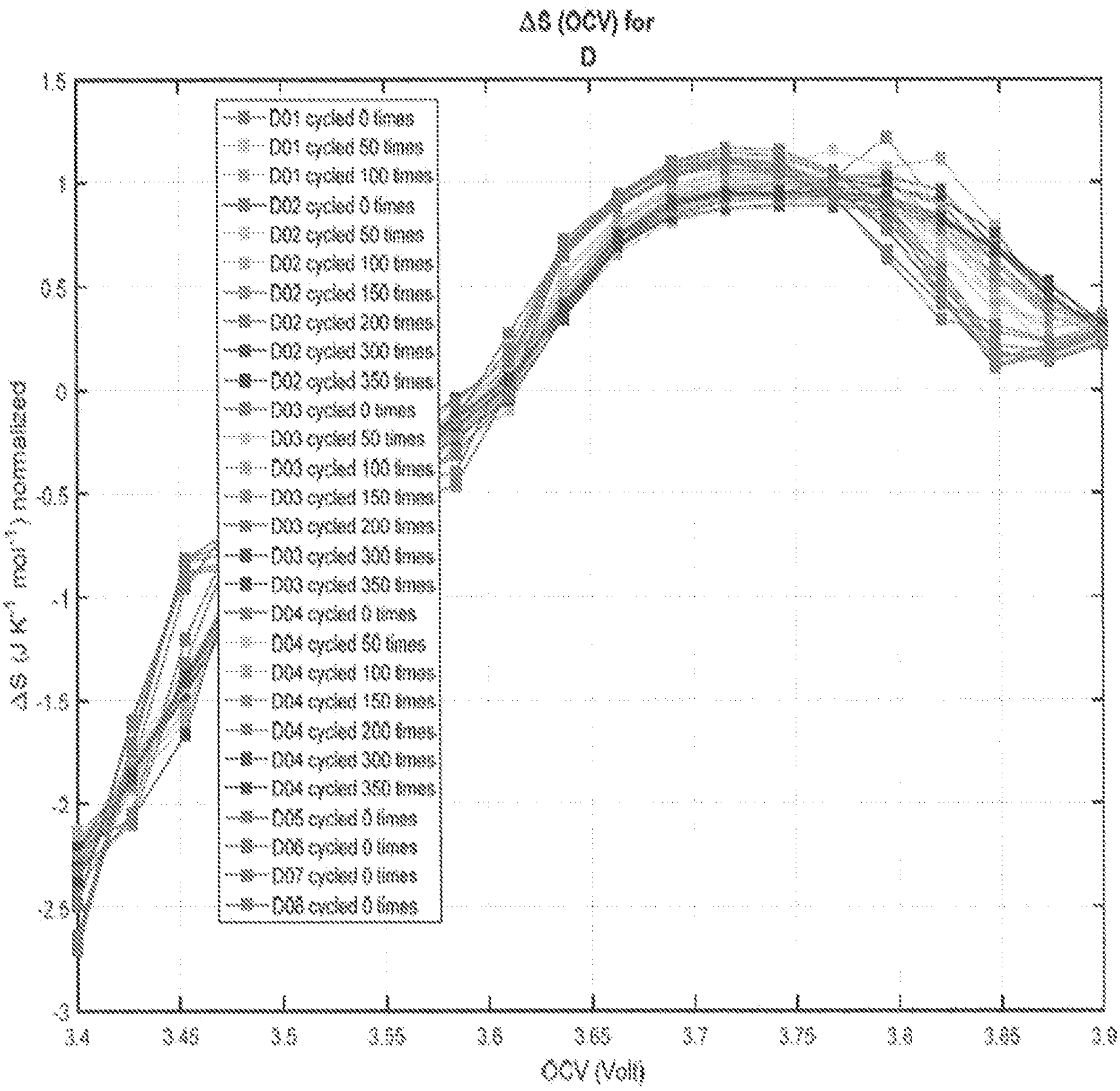
ΔS (OCV) for
D
ΔS (J K⁻¹ mol⁻¹) normalized
OCV (Volt)
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
3.4
3.45
3.5
3.55
3.6
3.65
3.7
3.75
3.8
3.85
3.9
D01 cycled 0 times
D01 cycled 50 times
D01 cycled 100 times
D02 cycled 0 times
D02 cycled 50 times
D02 cycled 100 times
D02 cycled 150 times
D02 cycled 200 times
D02 cycled 300 times
D02 cycled 350 times
D03 cycled 0 times
D03 cycled 50 times
D03 cycled 100 times
D03 cycled 150 times
D03 cycled 200 times
D03 cycled 300 times
D03 cycled 350 times
D04 cycled 0 times
D04 cycled 50 times
D04 cycled 100 times
D04 cycled 150 times
D04 cycled 200 times
D04 cycled 300 times
D04 cycled 350 times
D05 cycled 0 times
D06 cycled 0 times
D07 cycled 0 times
D08 cycled 0 times

FIG.5

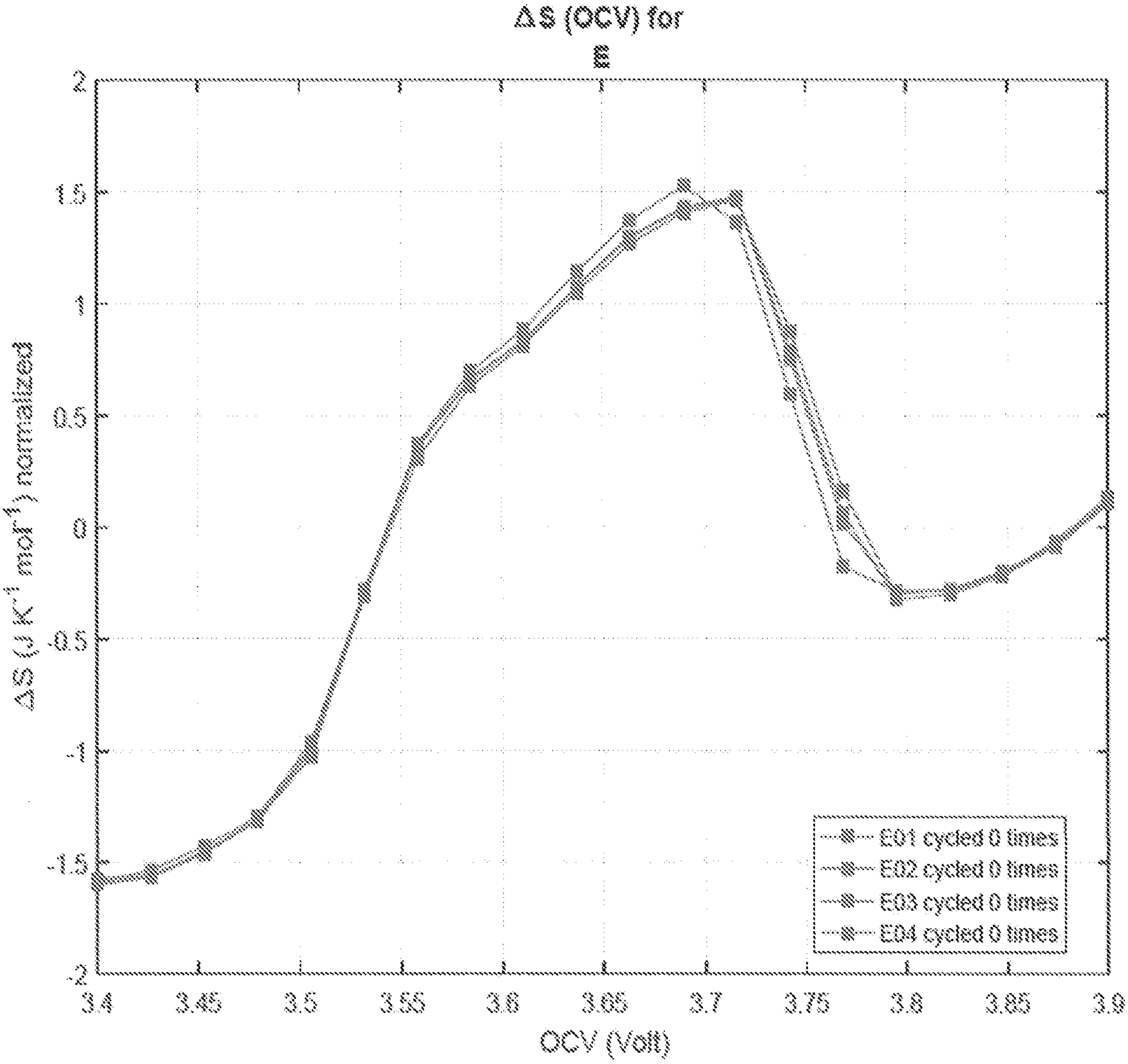
ΔS (OCV) for
E
ΔS (J K-1 mol-1) normalized
OCV (Volt)
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
3.4
3.45
3.5
3.55
3.6
3.65
3.7
3.75
3.8
3.85
3.9
E01 cycled 0 times
E02 cycled 0 times
E03 cycled 0 times
E04 cycled 0 times

FIG.6

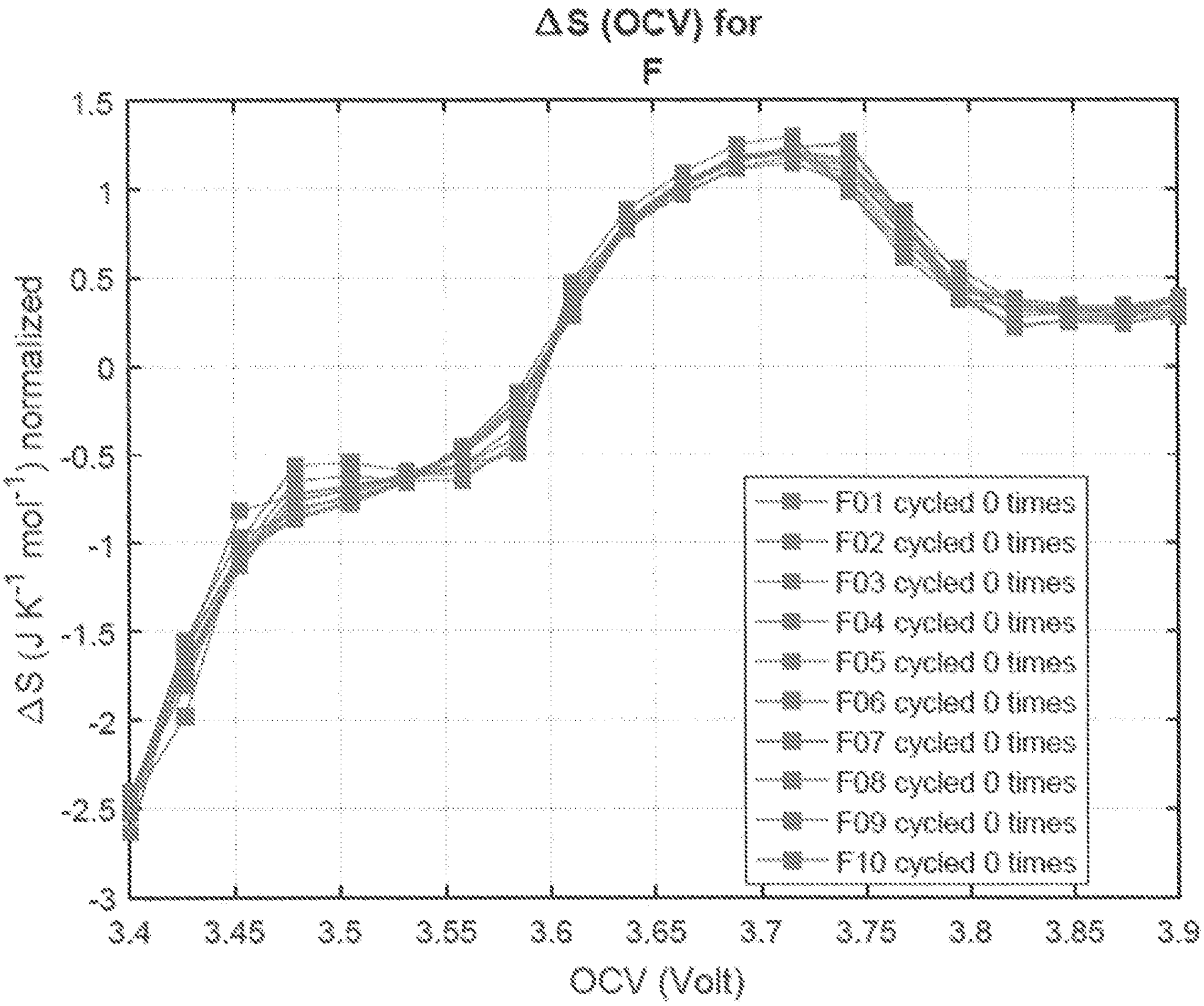
ΔS (OCV) for
F
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
ΔS (J K-1 mol-1) normalized
3.4
3.45
3.5
3.55
3.6
3.65
3.7
3.75
3.8
3.85
3.9
OCV (Volt)
F01 cycled 0 times
F02 cycled 0 times
F03 cycled 0 times
F04 cycled 0 times
F05 cycled 0 times
F06 cycled 0 times
F07 cycled 0 times
F08 cycled 0 times
F09 cycled 0 times
F10 cycled 0 times

FIG.7

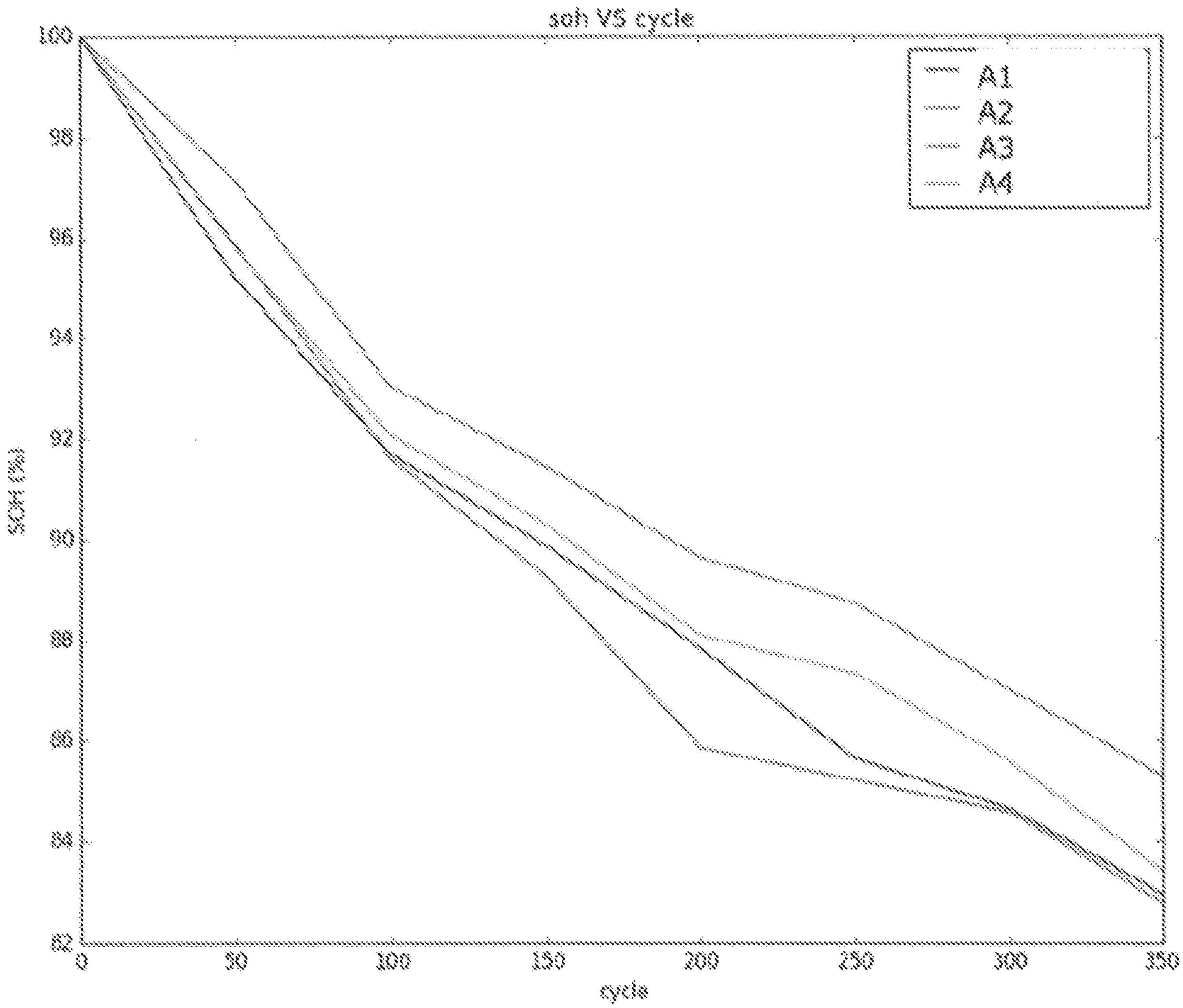
soh VS cycle
100
98
96
94
92
90
88
86
84
82
SOH (%)
0
50
100
150
200
250
300
350
cycle
A1
A2
A3
A4

FIG.8

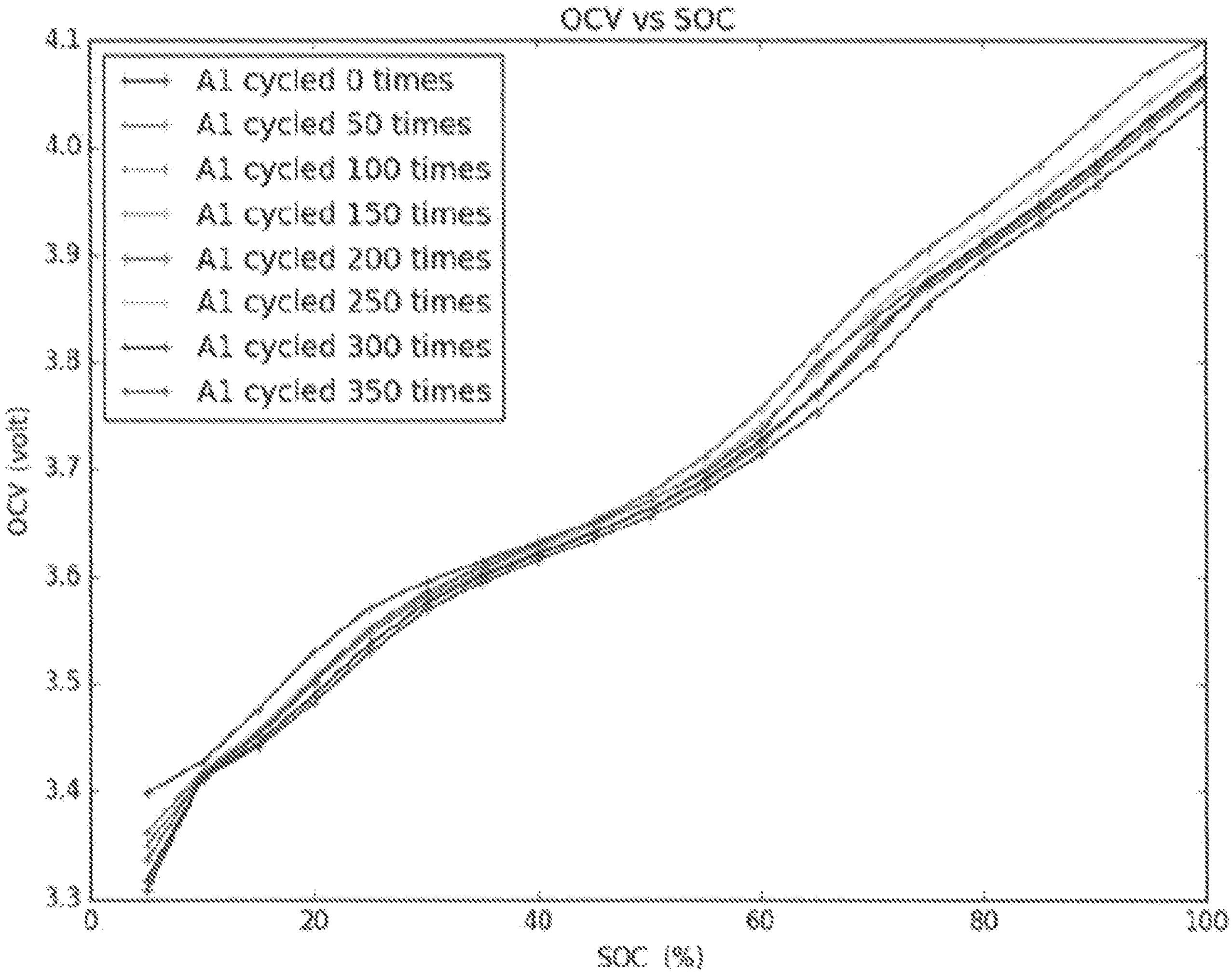
OCV vs SOC
A1 cycled 0 times
A1 cycled 50 times
A1 cycled 100 times
A1 cycled 150 times
A1 cycled 200 times
A1 cycled 250 times
A1 cycled 300 times
A1 cycled 350 times
OCV (volt)
SOC (%)
4.1
4.0
3.9
3.8
3.7
3.6
3.5
3.4
3.3
0
20
40
60
80
100

FIG.9

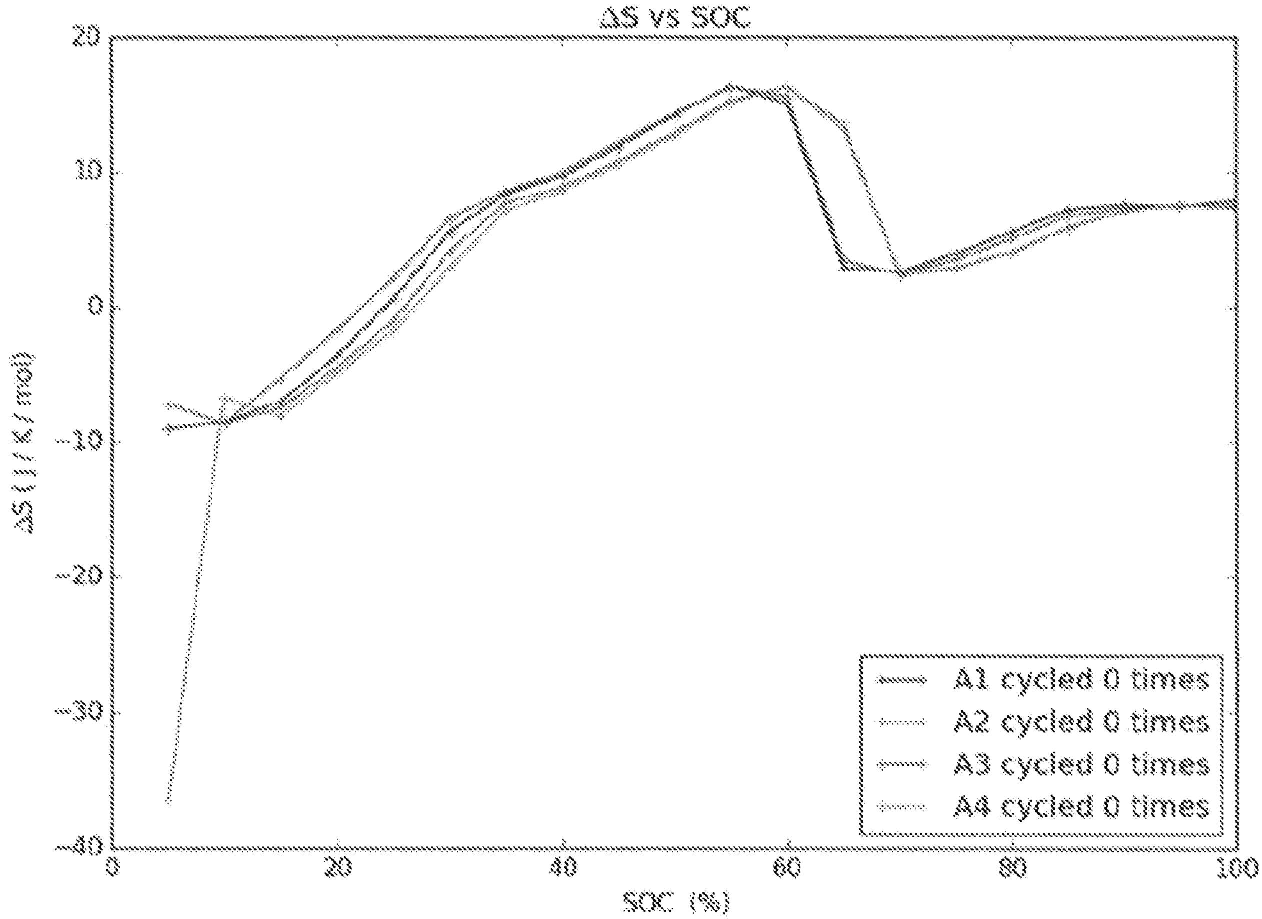
ΔS vs SOC
20
10
0
−10
−20
−30
−40
ΔS (J / K / mol)
0
20
40
60
80
100
SOC (%)
A1 cycled 0 times
A2 cycled 0 times
A3 cycled 0 times
A4 cycled 0 times

FIG.10

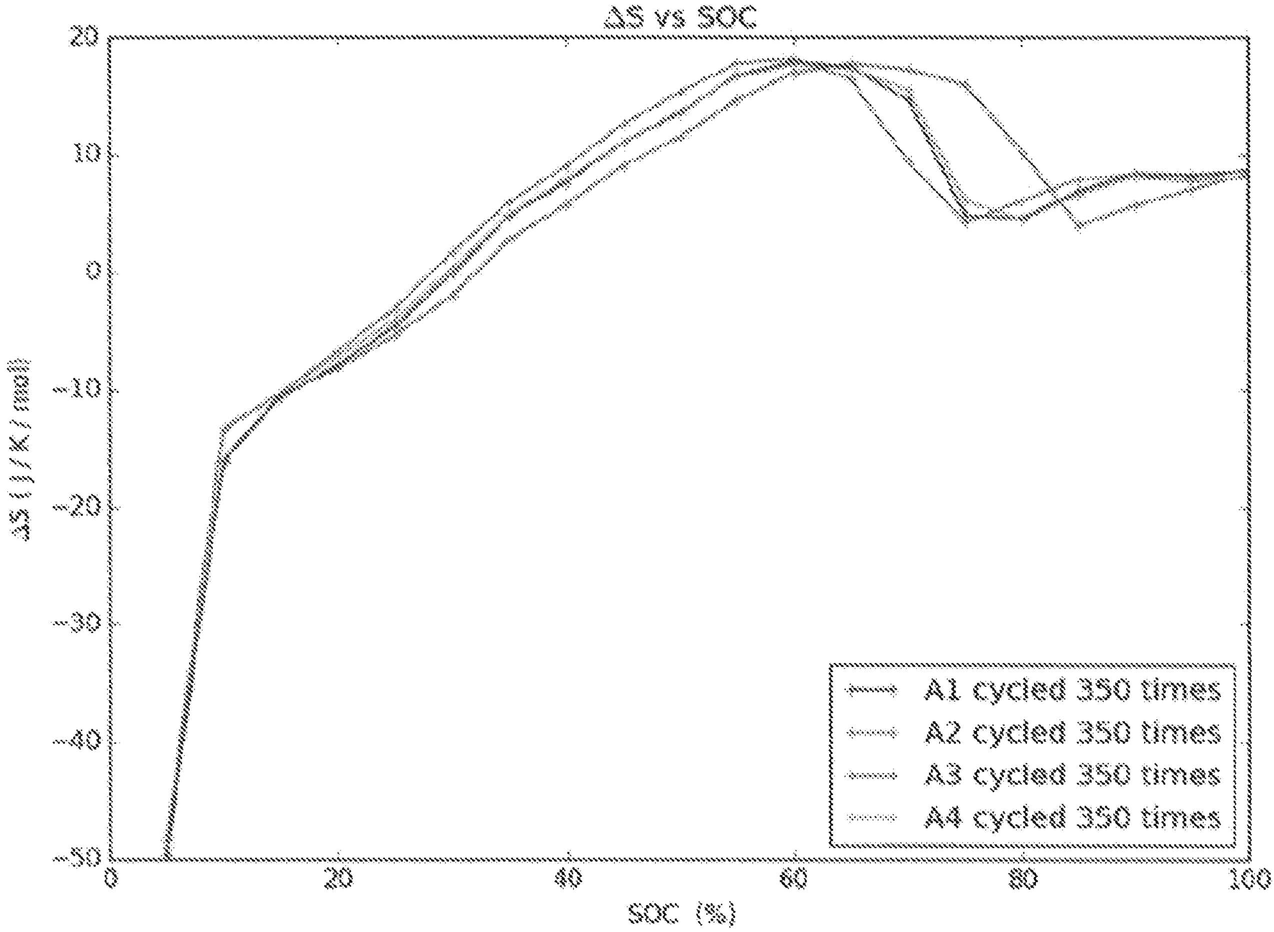
ΔS vs SOC
20
10
0
−10
−20
−30
−40
−50
ΔS (J / K / mol)
0
20
40
60
80
100
SOC (%)
A1 cycled 350 times
A2 cycled 350 times
A3 cycled 350 times
A4 cycled 350 times

FIG.11

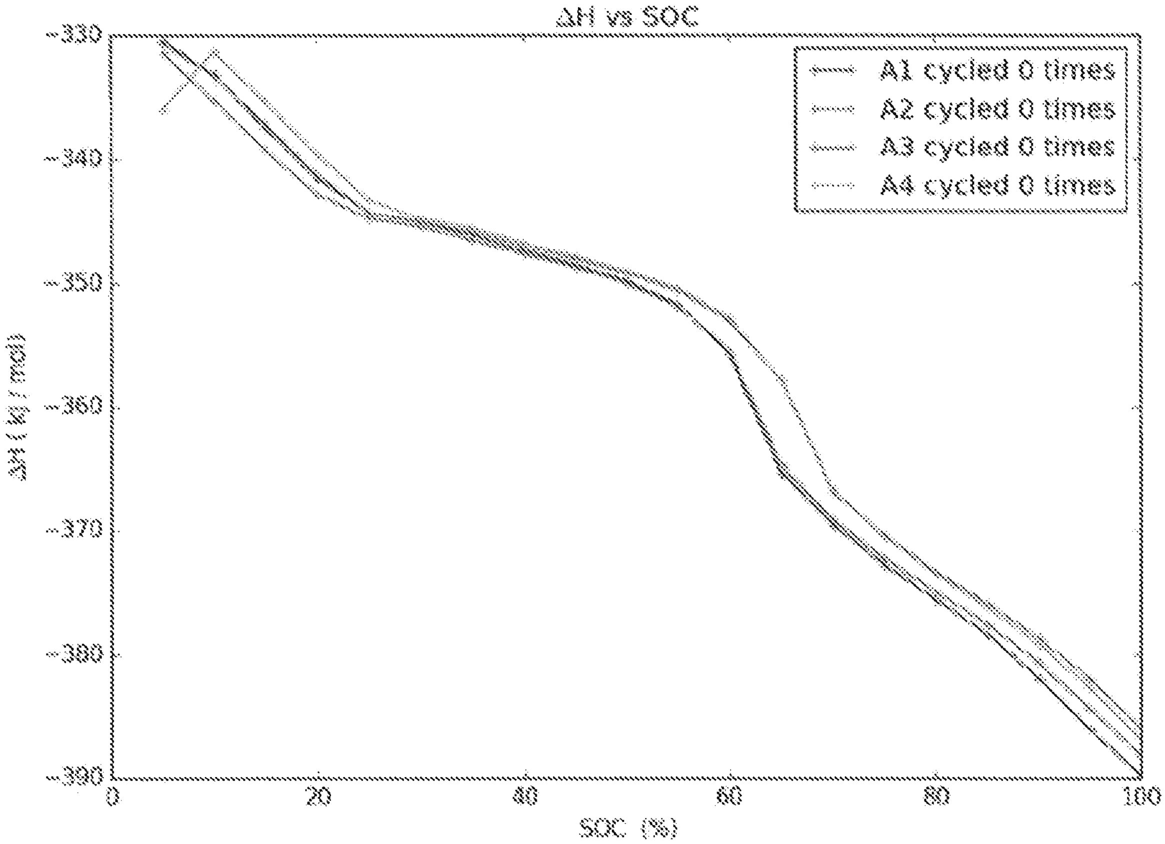
ΔH vs SOC
A1 cycled 0 times
A2 cycled 0 times
A3 cycled 0 times
A4 cycled 0 times
ΔH (kJ / mol)
−330
−340
−350
−360
−370
−380
−390
0
20
40
60
80
100
SOC (%)

FIG.12

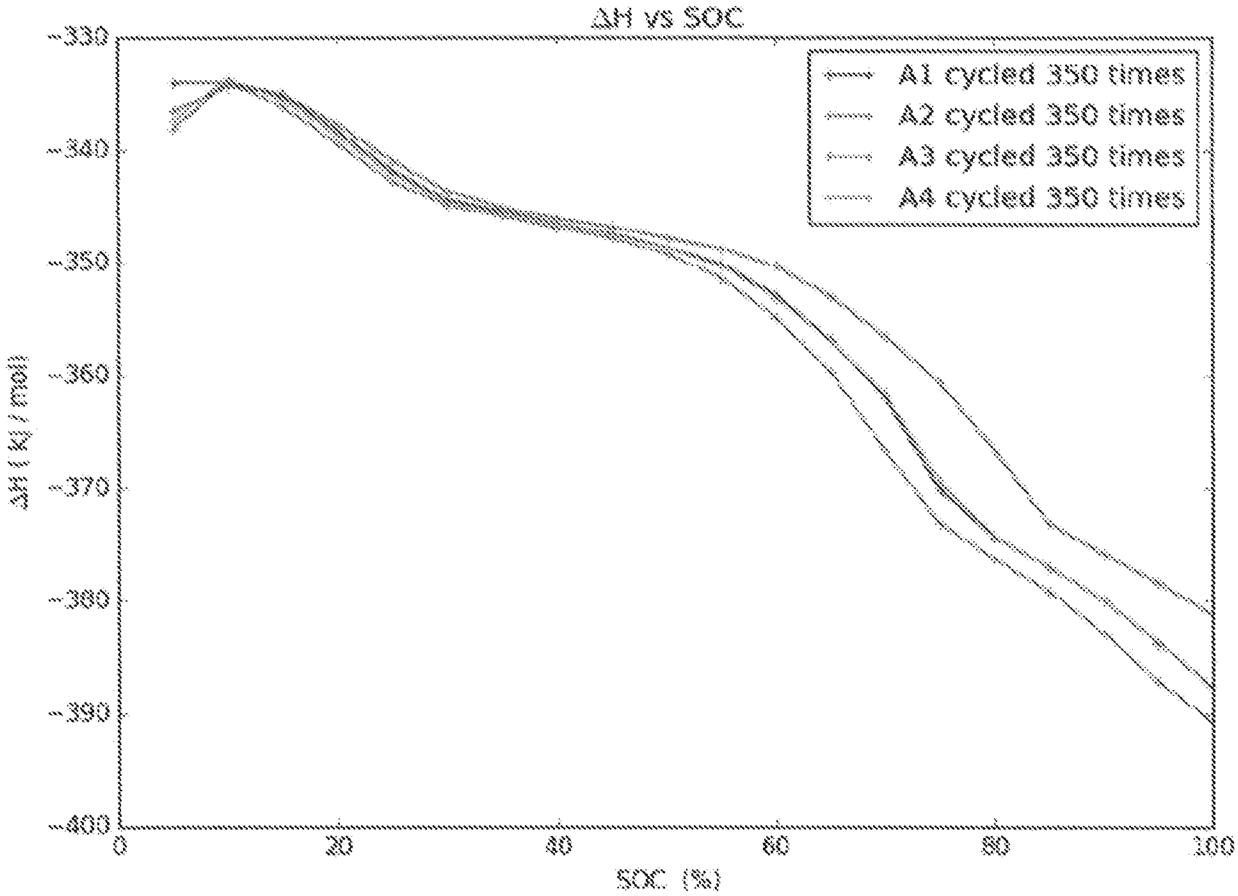
ΔH vs SOC
-330
-340
-350
-360
-370
-380
-390
-400
ΔH (kJ / mol)
0
20
40
60
80
100
SOC (%)
A1 cycled 350 times
A2 cycled 350 times
A3 cycled 350 times
A4 cycled 350 times

FIG.13

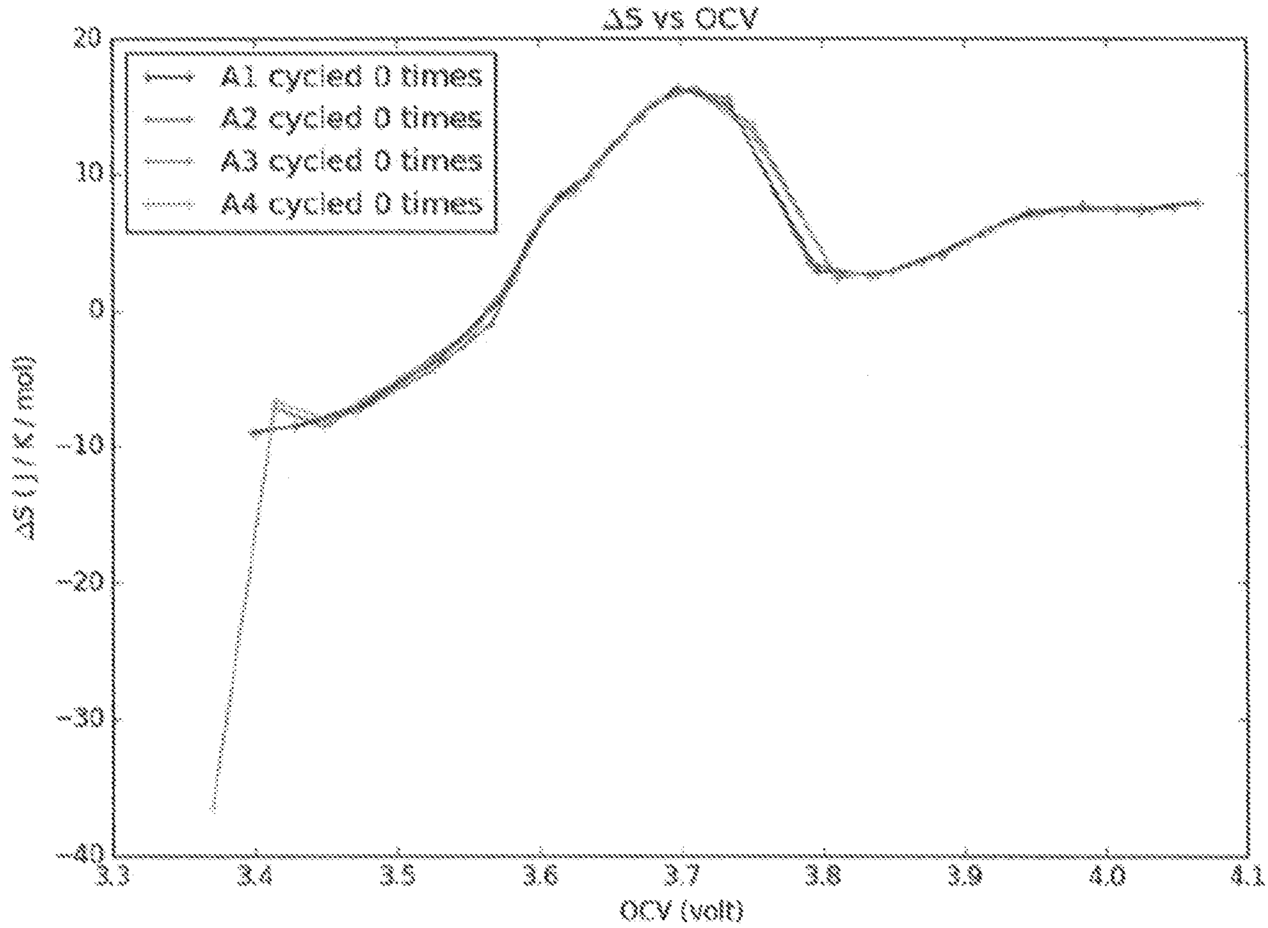
ΔS vs OCV
A1 cycled 0 times
A2 cycled 0 times
A3 cycled 0 times
A4 cycled 0 times
20
10
0
−10
−20
−30
−40
ΔS (J / K / mol)
3.3
3.4
3.5
3.6
3.7
3.8
3.9
4.0
4.1
OCV (volt)

FIG.14

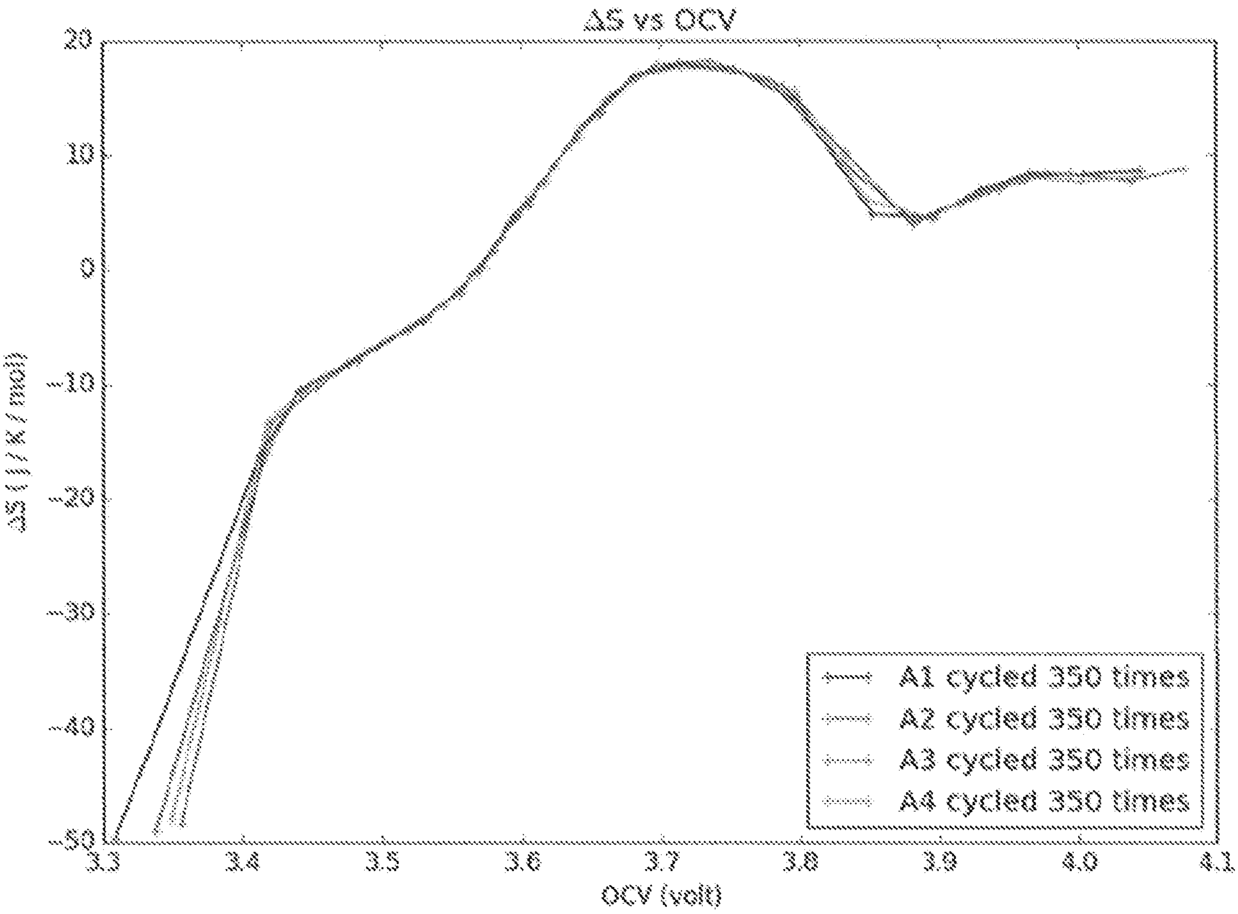
ΔS vs OCV
20
10
0
−10
−20
−30
−40
−50
ΔS (J / K / mol)
3.3
3.4
3.5
3.6
3.7
3.8
3.9
4.0
4.1
OCV (volt)
A1 cycled 350 times
A2 cycled 350 times
A3 cycled 350 times
A4 cycled 350 times

FIG.15

5

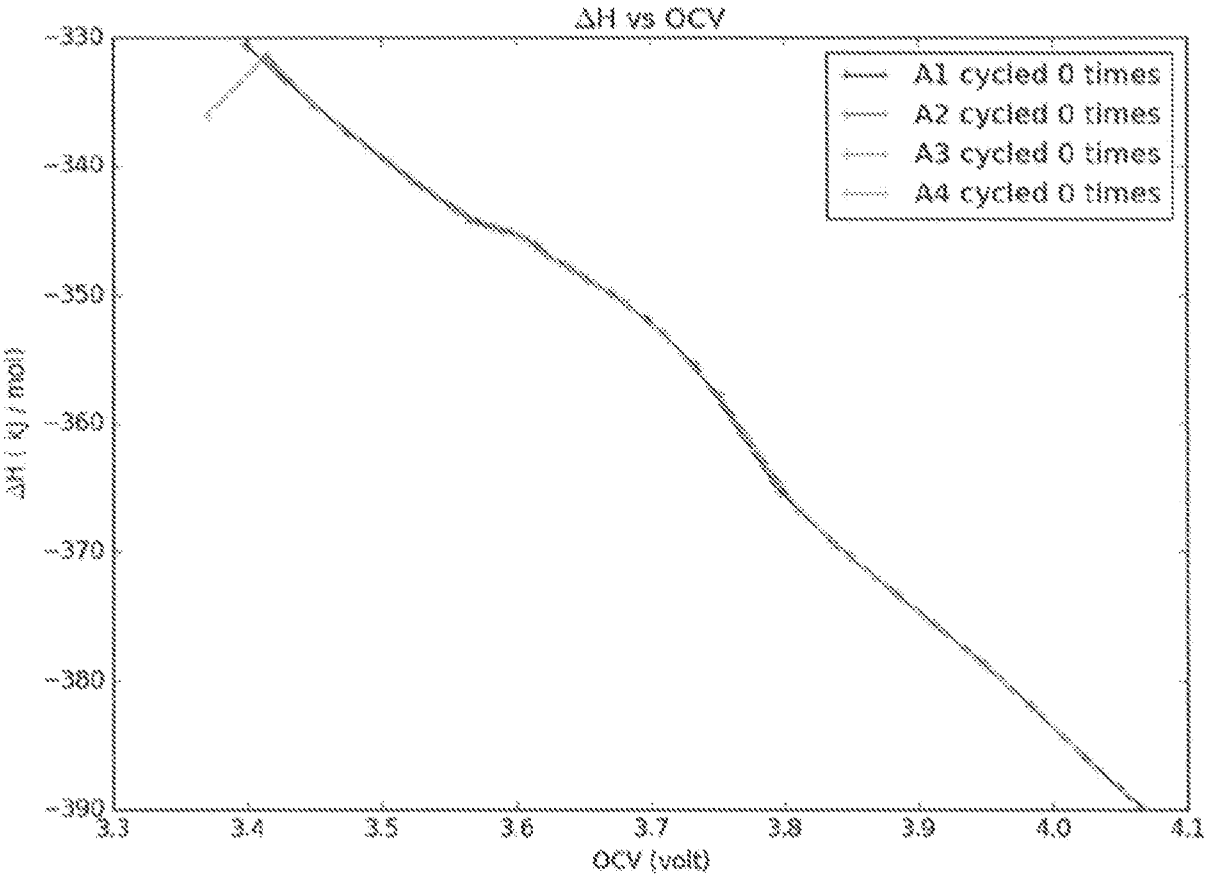
ΔH vs OCV
A1 cycled 0 times
A2 cycled 0 times
A3 cycled 0 times
A4 cycled 0 times
−330
−340
−350
−360
−370
−380
−390
ΔH (kJ / mol)
3.3
3.4
3.5
3.6
3.7
3.8
3.9
4.0
4.1
OCV (volt)

FIG.16

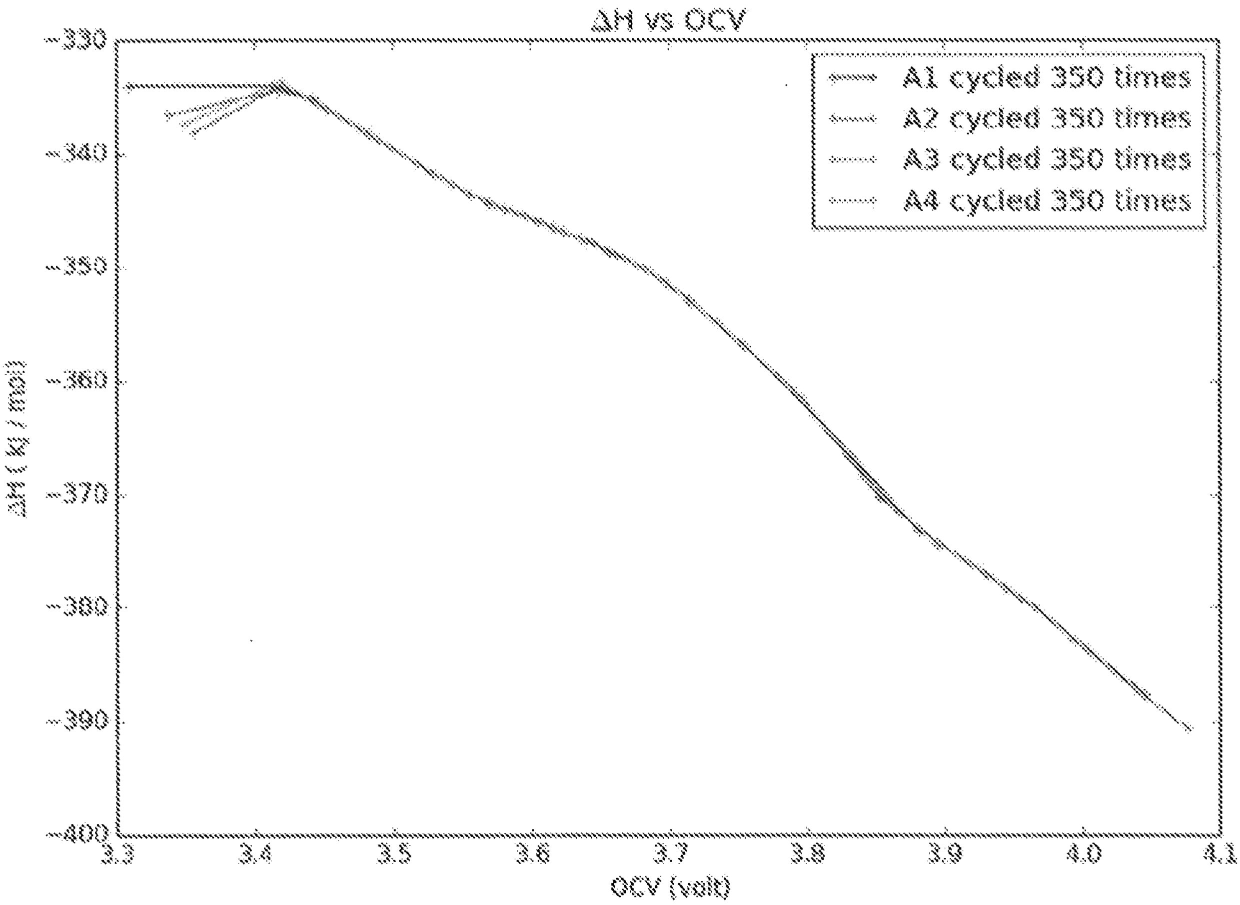
ΔH vs OCV
A1 cycled 350 times
A2 cycled 350 times
A3 cycled 350 times
A4 cycled 350 times
ΔH (kJ / mol)
OCV (volt)
−330
−340
−350
−360
−370
−380
−390
−400
3.3
3.4
3.5
3.6
3.7
3.8
3.9
4.0
4.1

FIG.17

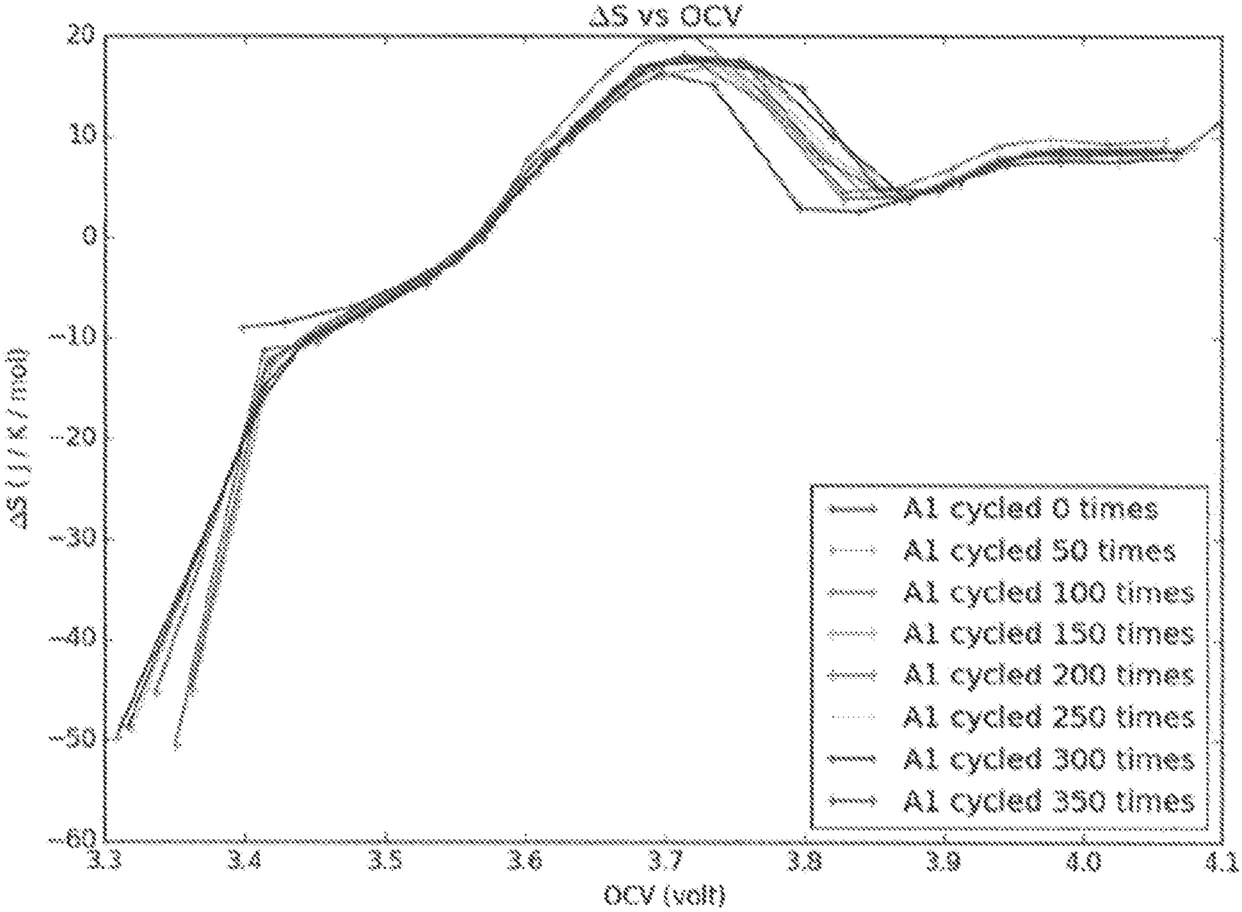
ΔS vs OCV
ΔS (J / K / mol)
OCV (volt)
20
10
0
−10
−20
−30
−40
−50
−60
3.3
3.4
3.5
3.6
3.7
3.8
3.9
4.0
4.1
A1 cycled 0 times
A1 cycled 50 times
A1 cycled 100 times
A1 cycled 150 times
A1 cycled 200 times
A1 cycled 250 times
A1 cycled 300 times
A1 cycled 350 times

FIG.18

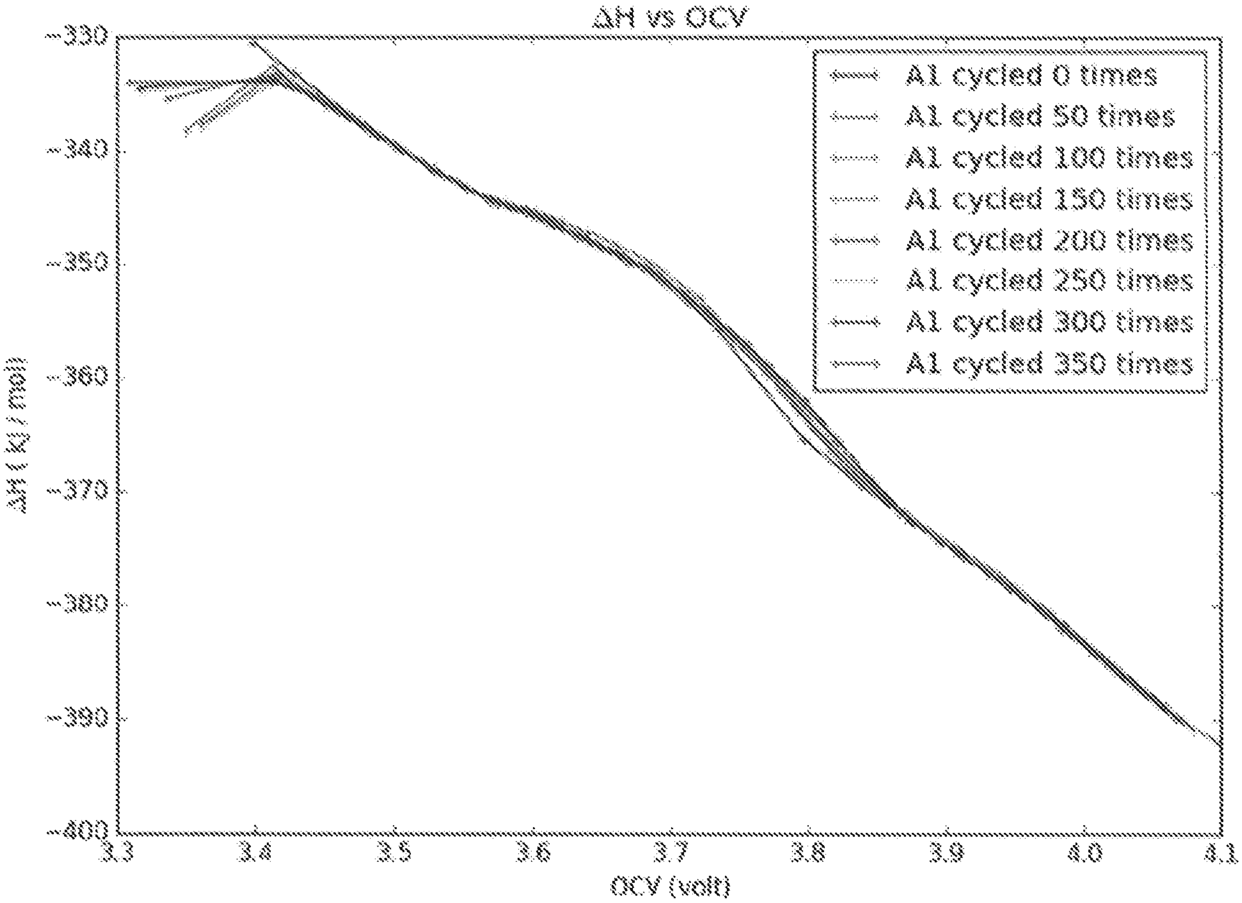
ΔH vs OCV
-330
-340
-350
-360
-370
-380
-390
-400
ΔH (kJ / mol)
3.3
3.4
3.5
3.6
3.7
3.8
3.9
4.0
4.1
OCV (volt)
A1 cycled 0 times
A1 cycled 50 times
A1 cycled 100 times
A1 cycled 150 times
A1 cycled 200 times
A1 cycled 250 times
A1 cycled 300 times
A1 cycled 350 times

FIG.19

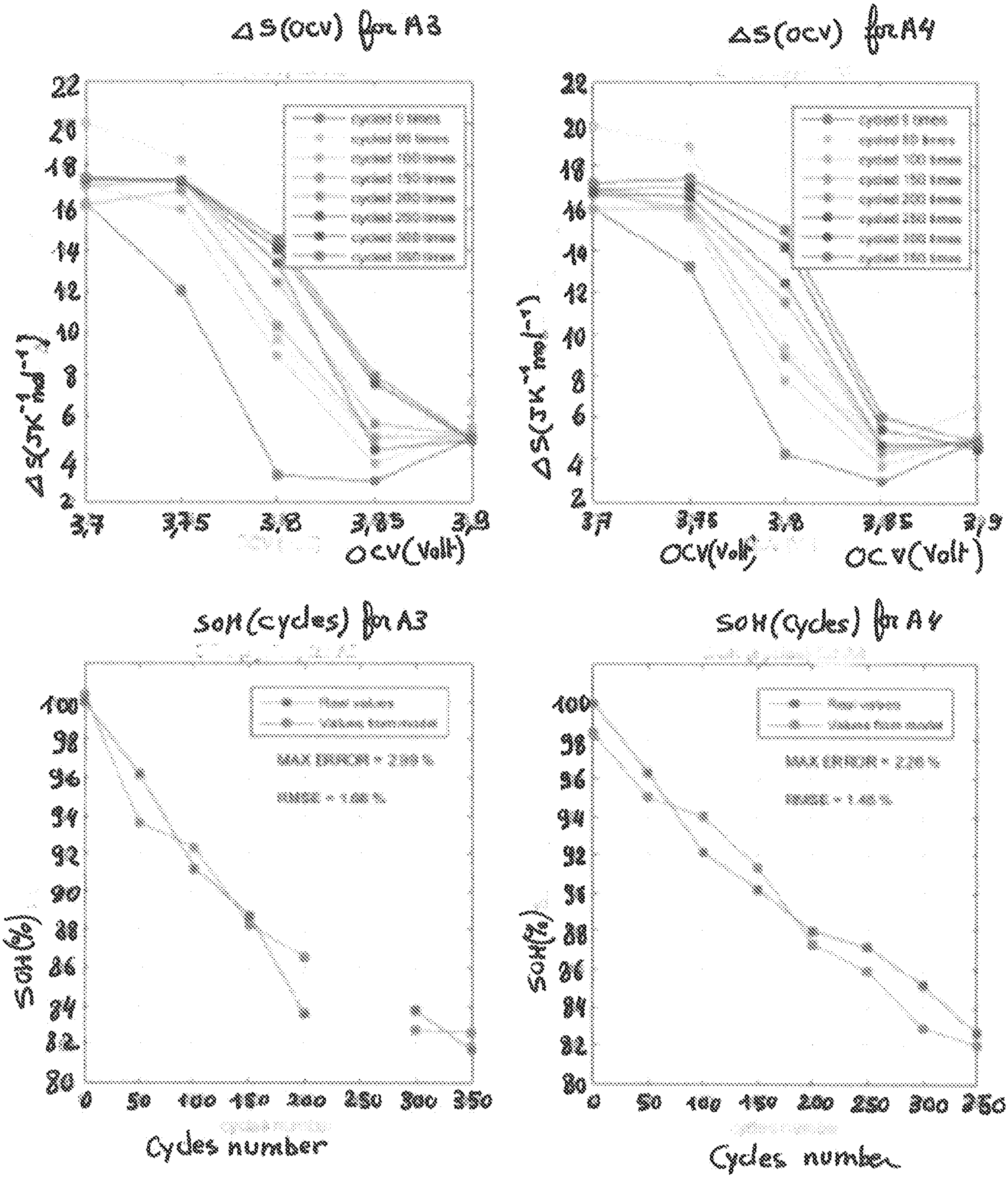
ΔS(OCV) for A3
ΔS(OCV) for A4
ΔS(JK⁻¹mol⁻¹)
OCV(Volt)
SOH(Cycles) for A3
SOH(Cycles) for A4
SOH(%)
Cycles number

FIG.20

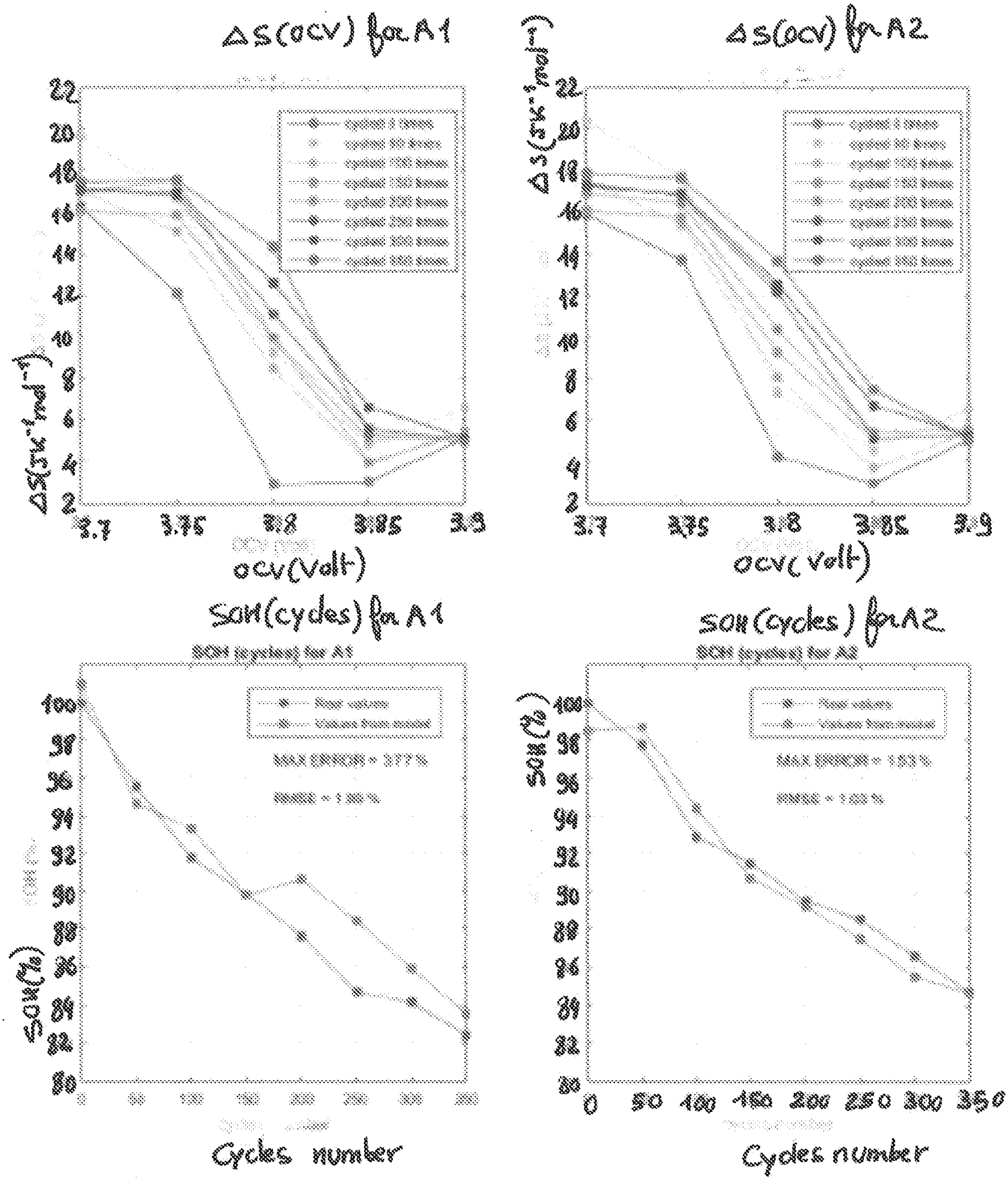
ΔS(OCV) for A1
ΔS(JK⁻¹mol⁻¹)
OCV(Volt)
ΔS(OCV) for A2
ΔS(JK⁻¹mol⁻¹)
OCV(Volt)
SOH(cycles) for A1
SOH(%)
Cycles number
SOH(cycles) for A2
SOH(%)
Cycles number

FIG 20 (suite)

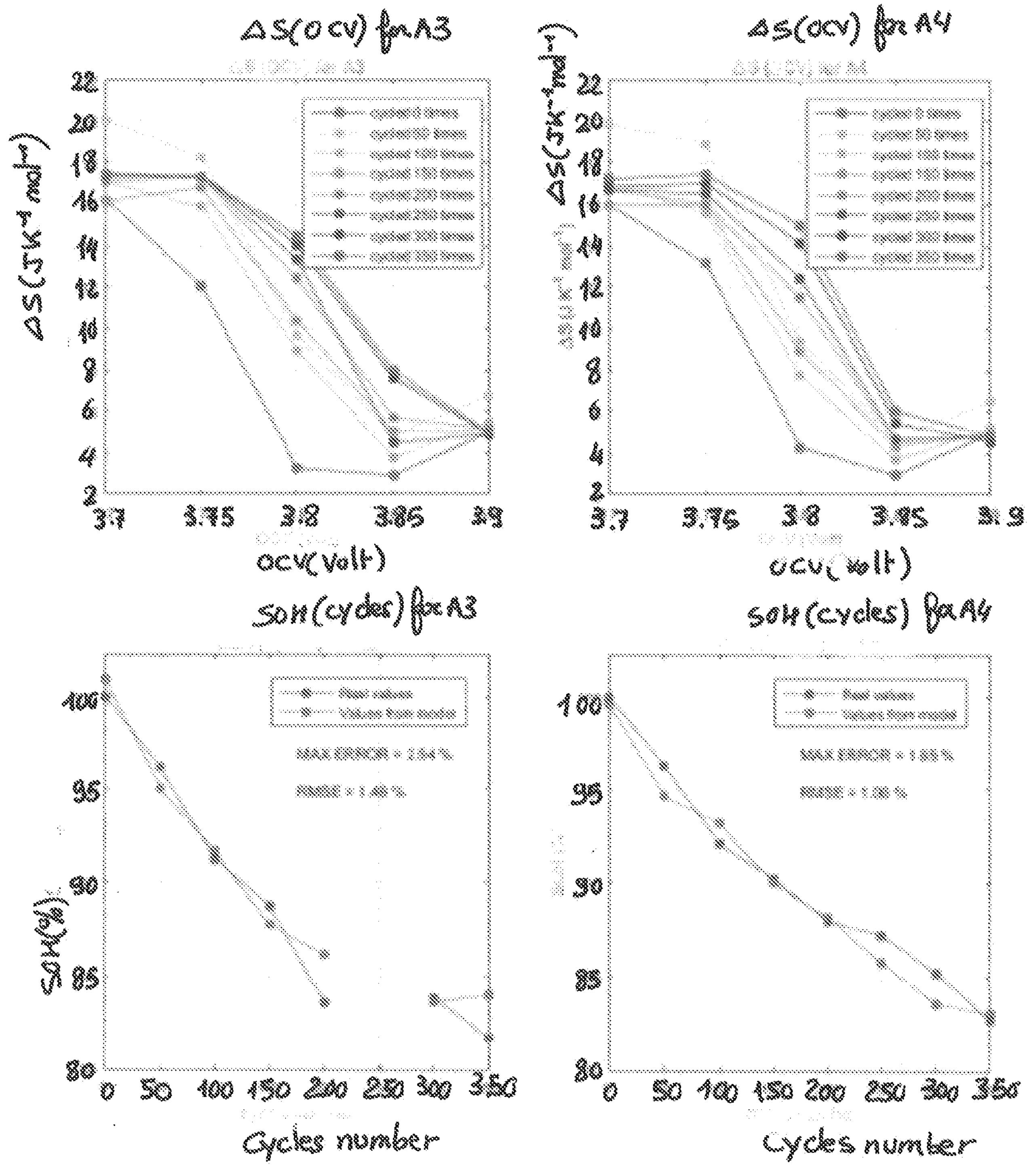
ΔS(OCV) for A3
ΔS(OCV) for A4
ΔS(JK⁻¹ mol⁻¹)
22
20
18
16
14
12
10
8
6
4
2
3.7
3.75
3.8
3.85
3.9
3.76
OCV(Volt)
SOH(cycles) for A3
SOH(cycles) for A4
SOH(%)
100
95
90
85
80
0
50
100
150
200
250
300
350
Cycles number

FIG.21

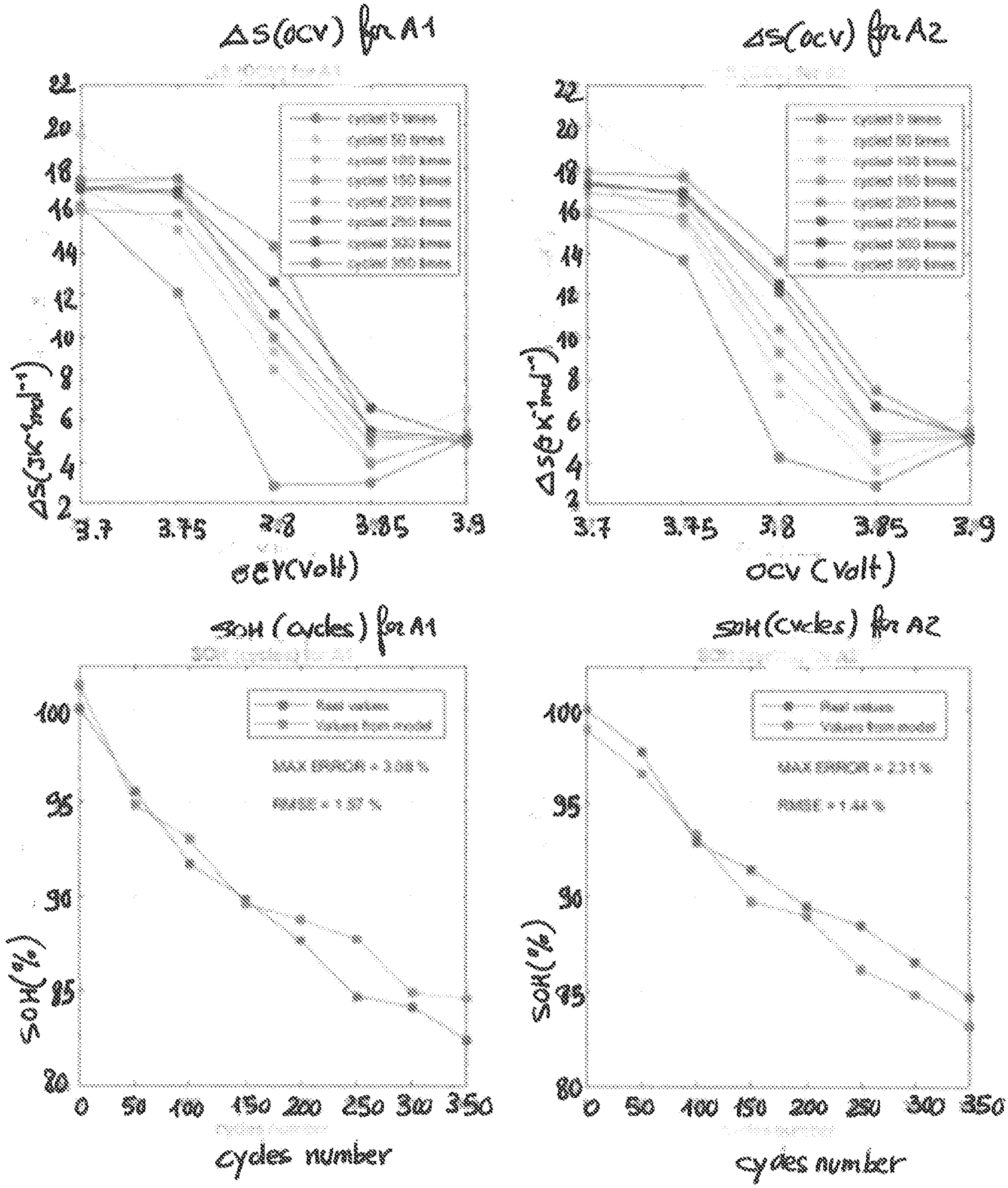
ΔS(OCV) for A1
ΔS(JK-1mol-1)
22
20
18
16
14
12
10
8
6
4
2
3.7
3.75
3.8
3.85
3.9
OCV(Volt)
ΔS(OCV) for A2
ΔS(JK-1mol-1)
OCV (Volt)
SOH (cycles) for A1
SOH(%)
100
95
90
85
80
0
50
100
150
200
250
300
350
cycles number
SOH(cycles) for A2
SOH(%)
cycles number

FIG.21 (suite)

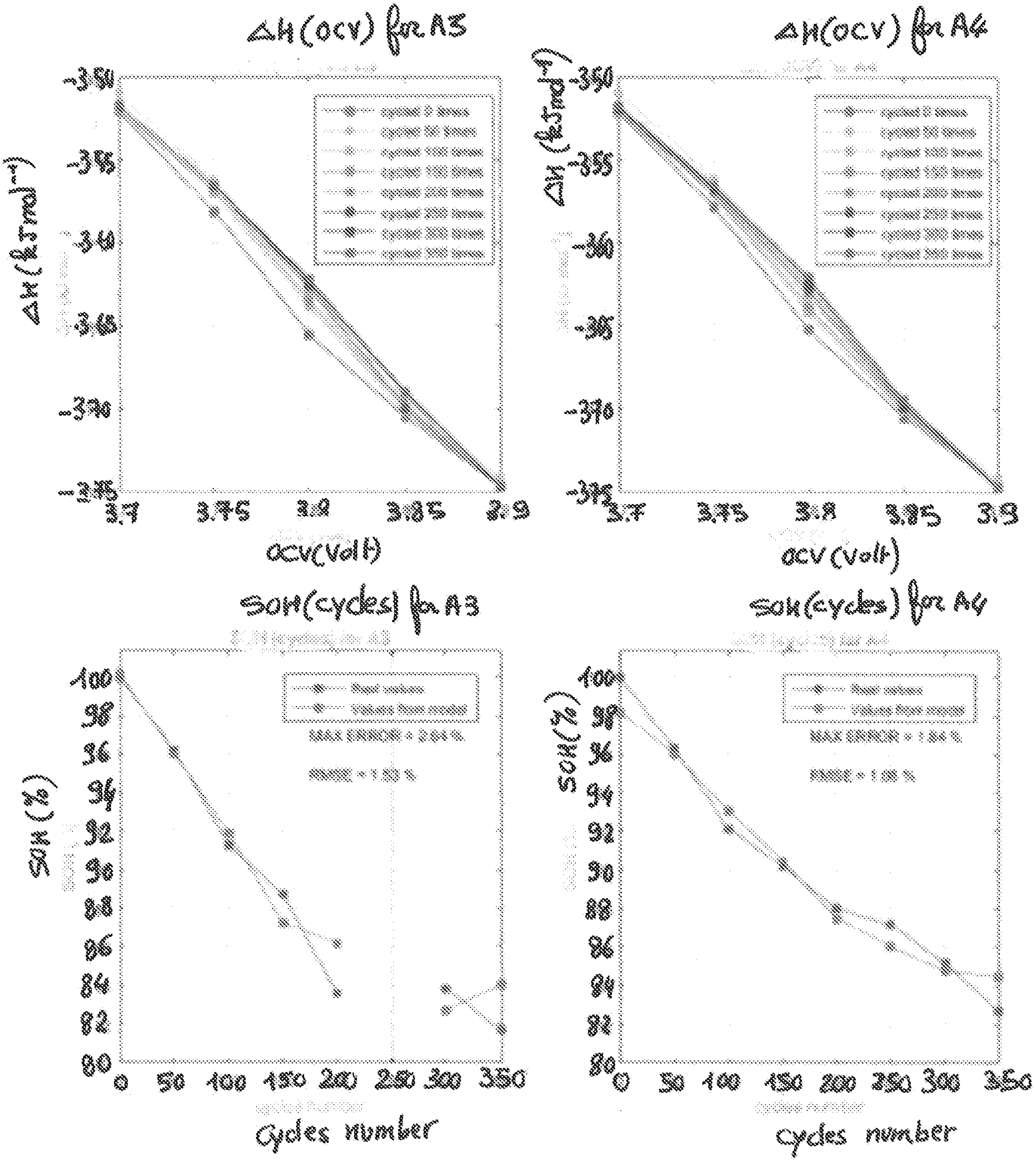
ΔH(OCV) for A3
ΔH(OCV) for A4
ΔH (kJ mol⁻¹)
-3.50
-3.55
-3.60
-3.65
-3.70
-3.75
3.7
3.75
3.8
3.85
3.9
OCV(Volt)
SOH(cycles) for A3
SOH(cycles) for A4
SOH (%)
100
98
96
94
92
90
88
86
84
82
80
0
50
100
150
200
250
300
350
Cycles number

FIG.22

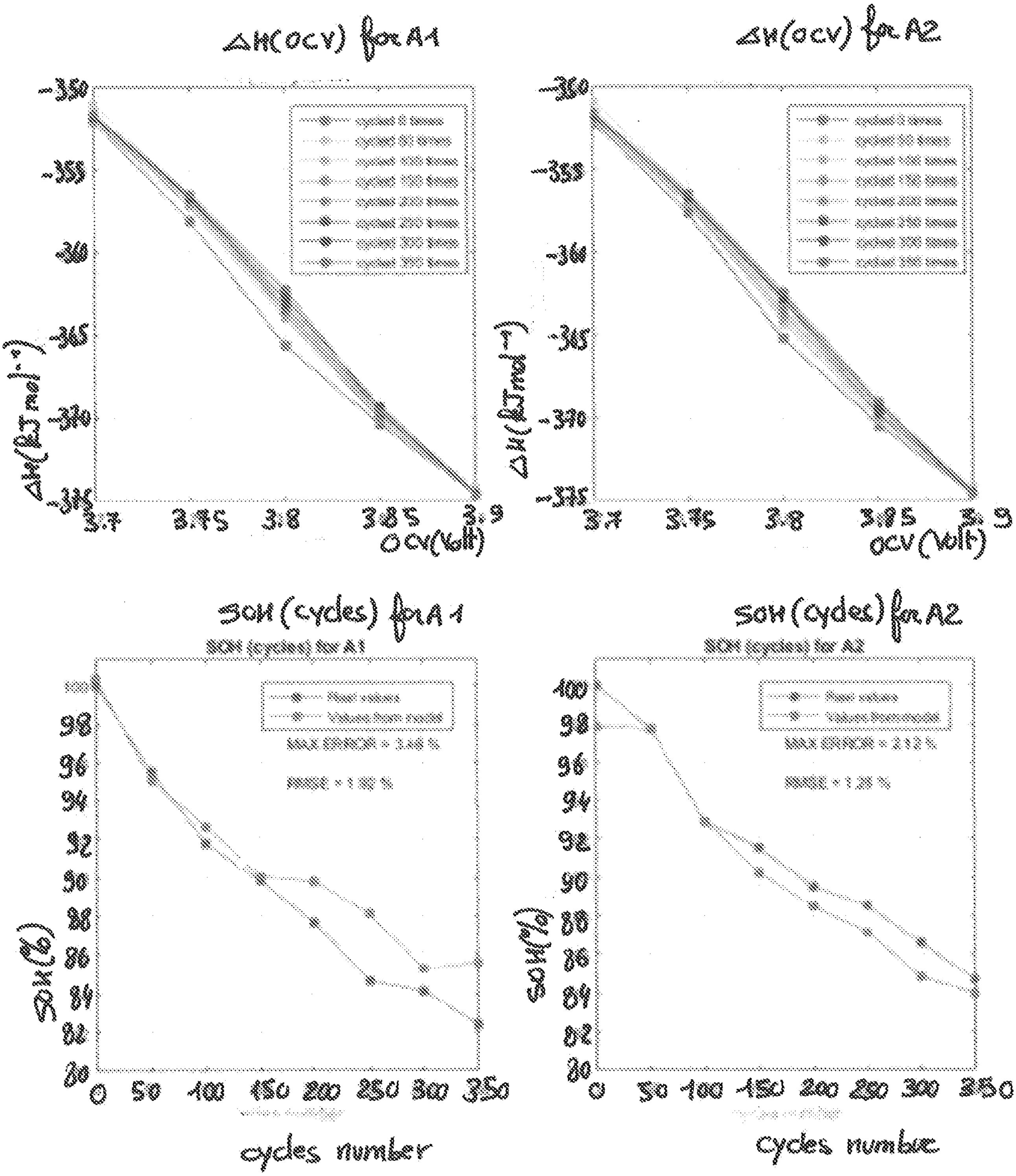
ΔH(OCV) for A1
ΔH(OCV) for A2
ΔH (kJ mol⁻¹)
OCV (Volt)
-350
-355
-360
-365
-370
-375
3.7
3.75
3.8
3.85
3.9
SOH (cycles) for A1
SOH (cycles) for A2
SOH (%)
cycles number
100
98
96
94
92
90
88
86
84
82
80
0
50
100
150
200
250
300
350

FIG.22 (suite)

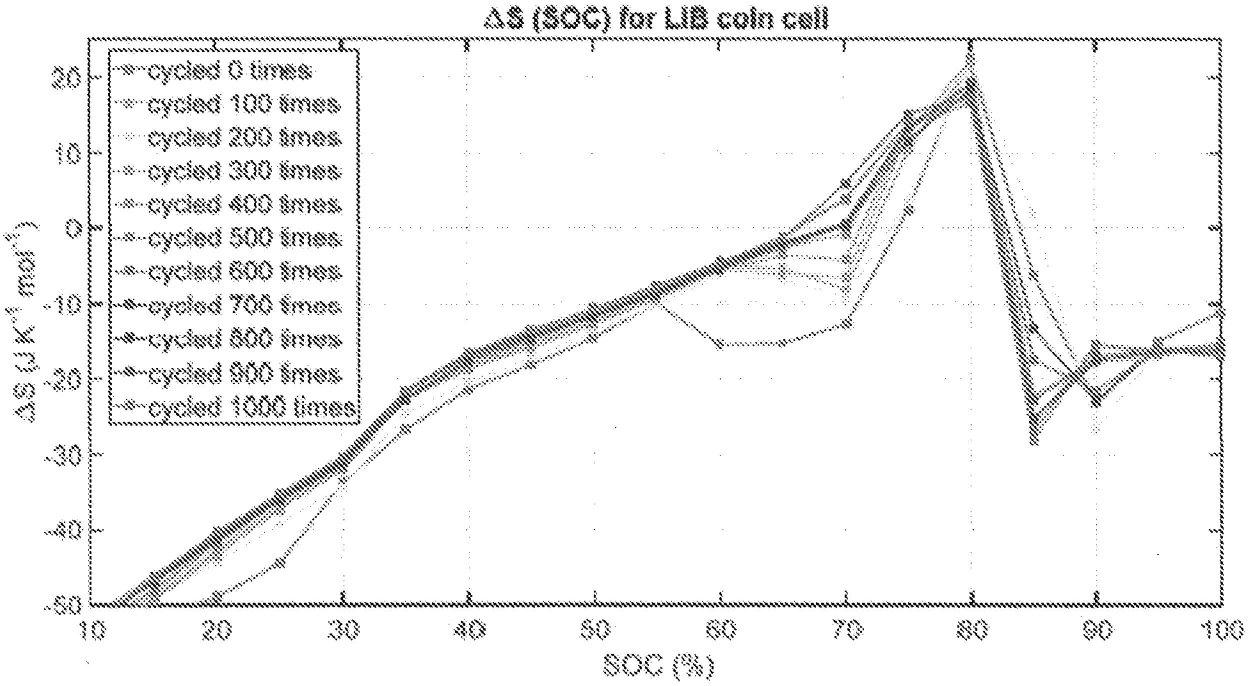
ΔS (SOC) for LIB coin cell
cycled 0 times
cycled 100 times
cycled 200 times
cycled 300 times
cycled 400 times
cycled 500 times
cycled 600 times
cycled 700 times
cycled 800 times
cycled 900 times
cycled 1000 times
ΔS (J K⁻¹ mol⁻¹)
SOC (%)
20
10
0
-10
-20
-30
-40
-50
10
20
30
40
50
60
70
80
90
100

FIG.23

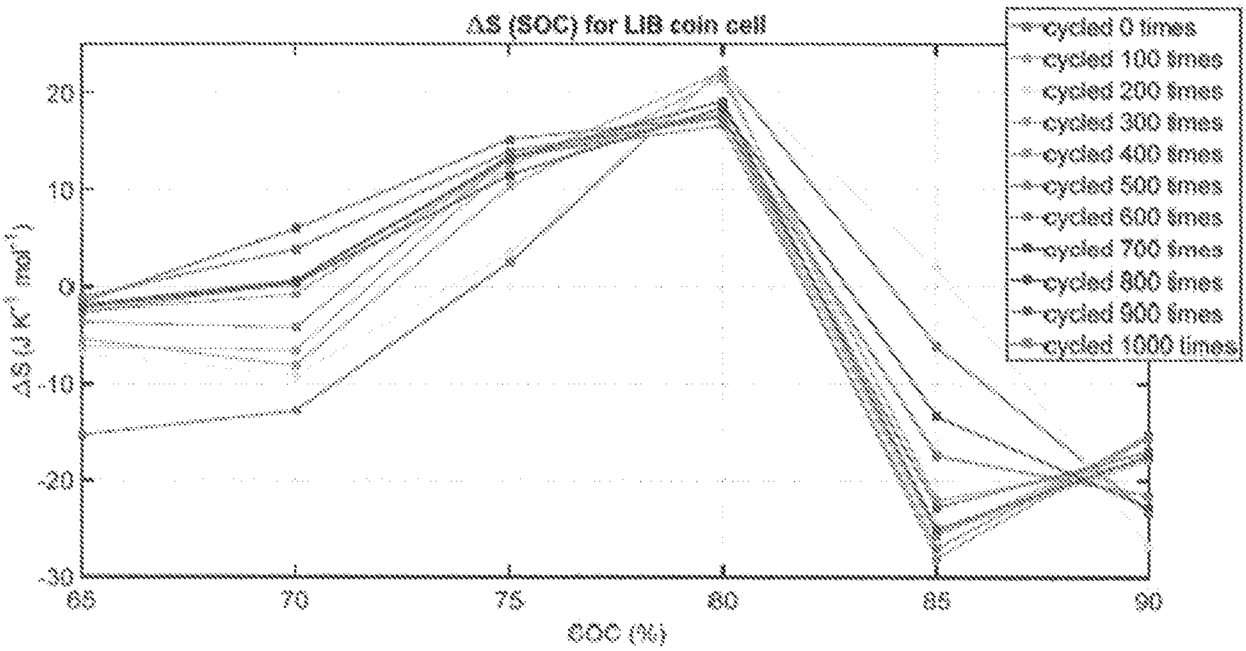
ΔS (SOC) for LIB coin cell
cycled 0 times
cycled 100 times
cycled 200 times
cycled 300 times
cycled 400 times
cycled 500 times
cycled 600 times
cycled 700 times
cycled 800 times
cycled 900 times
cycled 1000 times
20
10
0
-10
-20
-30
ΔS (J K⁻¹ mol⁻¹)
65
70
75
80
85
90
SOC (%)

FIG.24

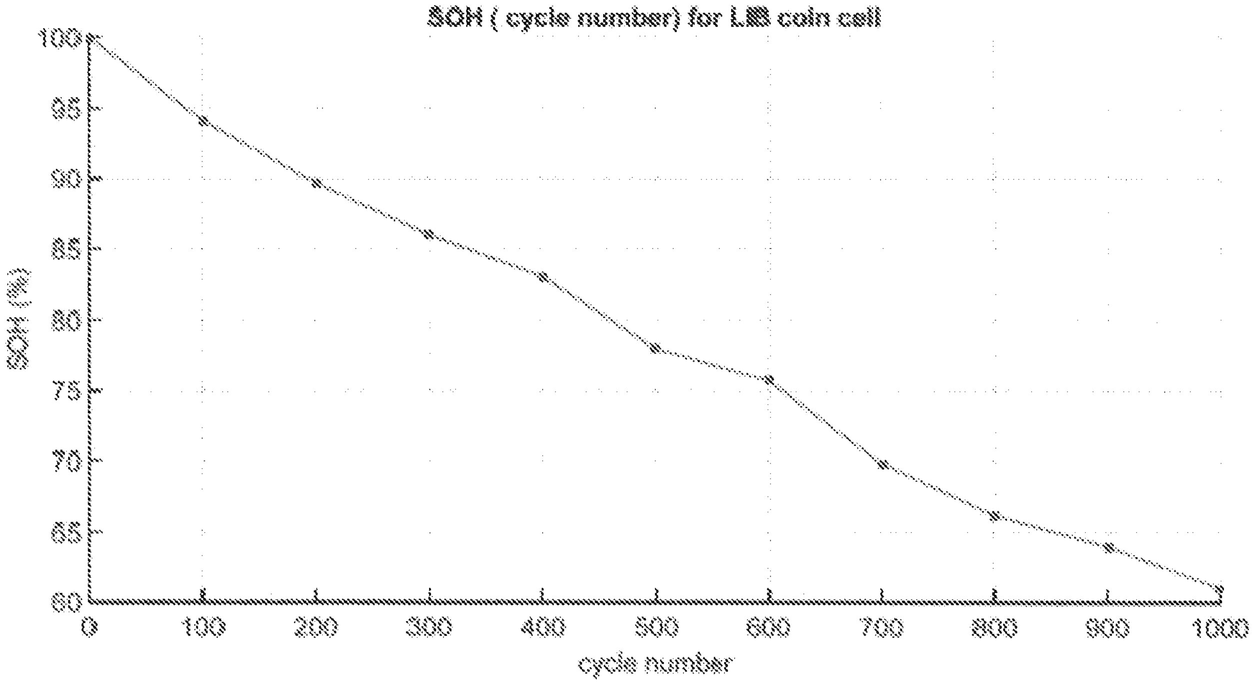
SOH (cycle number) for LIB coin cell
SOH (%)
100
95
90
85
80
75
70
65
60
0
100
200
300
400
500
600
700
800
900
1000
cycle number

FIG.25

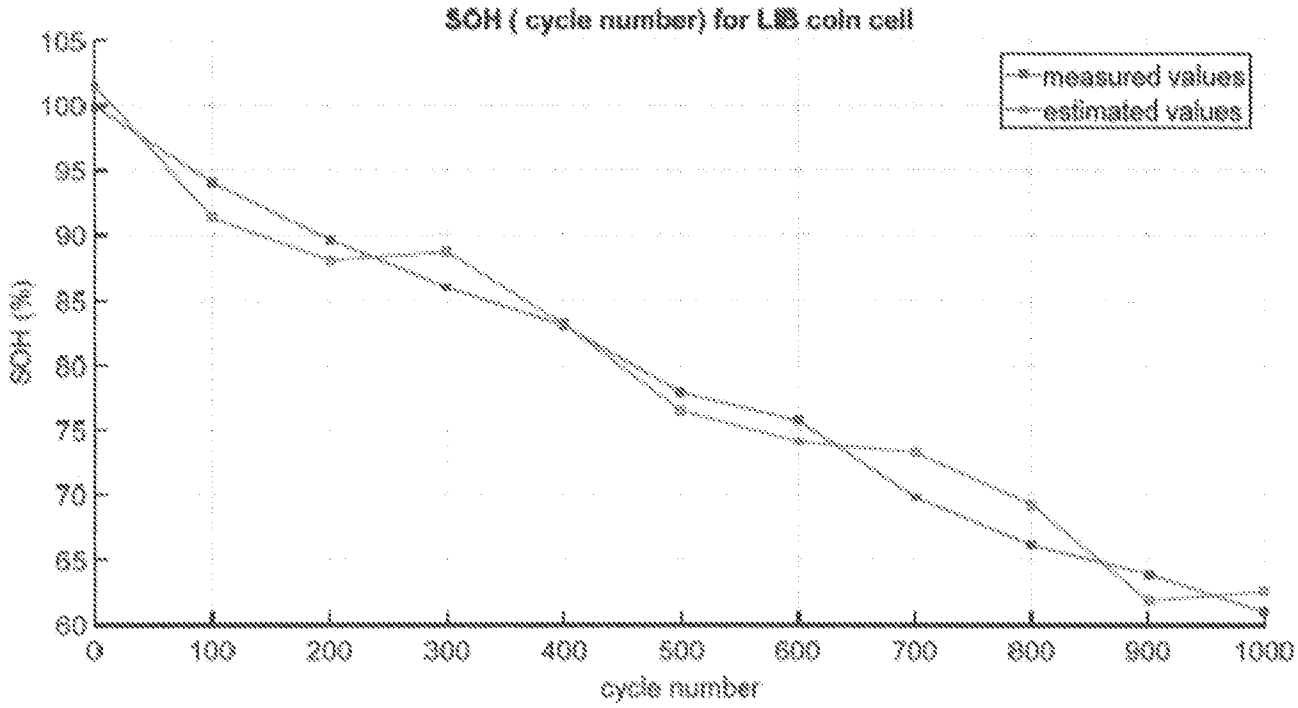
SOH (cycle number) for LIB coin cell
measured values
estimated values
SOH (%)
105
100
95
90
85
80
75
70
65
60
0
100
200
300
400
500
600
700
800
900
1000
cycle number

FIG.26

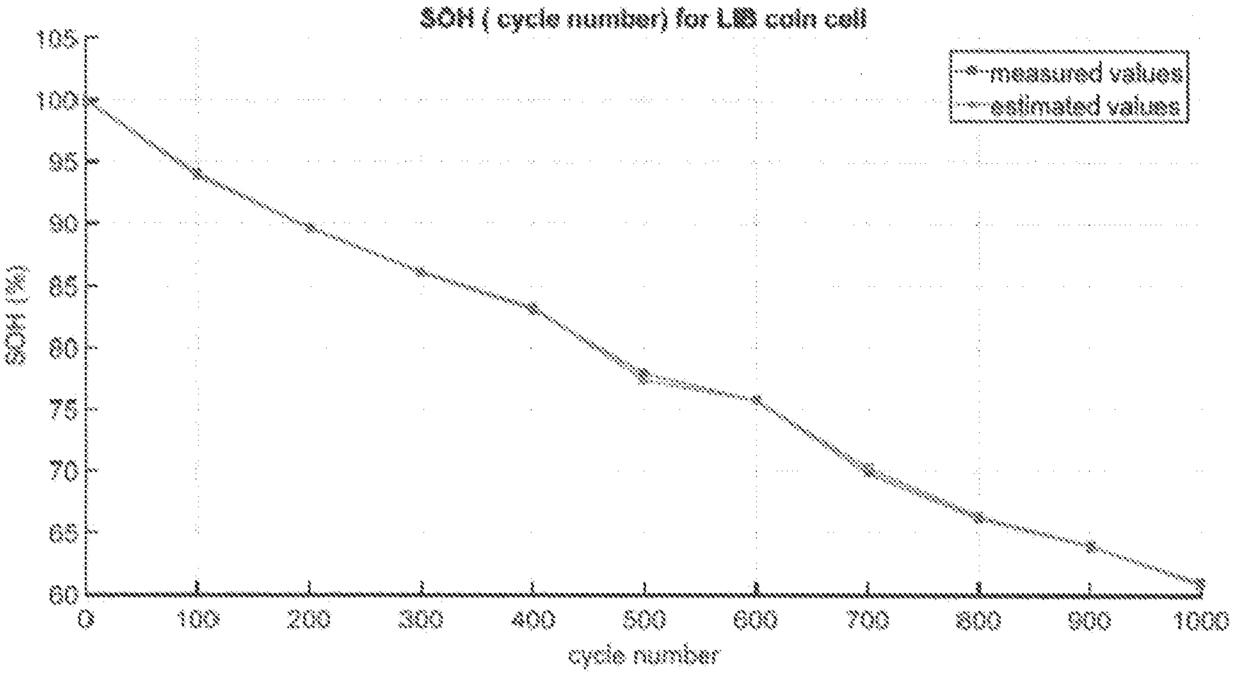
SOH (cycle number) for LIB coin cell
measured values
estimated values
105
100
95
90
85
80
75
70
65
60
SOH (%)
0
100
200
300
400
500
600
700
800
900
1000
cycle number

FIG.27

INTERNATIONAL SEARCH REPORT

International application No
PCT/IB2018/059755

A. CLASSIFICATION OF SUBJECT MATTER
INV. H01M10/42 H01M10/48 G01R31/367 G01R31/392
ADD. H01M10/44

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
H01M G01R

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal, WPI Data

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	EP 2 841 956 A2 (CALIFORNIA INST OF TECHN [US]; CENTRE NAT RECH SCIENT [FR] ET AL.) 4 March 2015 (2015-03-04) paragraph [0007] - paragraphs [0012], [0035] -----	1-26
X	WO 2010/105062 A1 (CALIFORNIA INST OF TECHN [US]; YAZAMI RACHID [US] ET AL.) 16 September 2010 (2010-09-16) paragraph [0008] - paragraph [0012] paragraph [0047] - paragraph [0049] paragraph [0060] - paragraph [0070] -----	1-26

☐ Further documents are listed in the continuation of Box C.

☒ See patent family annex.

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Date of the actual completion of the international search	Date of mailing of the international search report
19 March 2019	10/04/2019

Name and mailing address of the ISA/	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Topalov, Angel

1

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No

PCT/IB2018/059755

Patent document cited in search report		Publication date	Patent family member(s)			Publication date
EP 2841956	A2	04-03-2015	CN	104471415	A	25-03-2015
			EP	2841956	A2	04-03-2015
			JP	6368707	B2	01-08-2018
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			US	2013322488	A1	05-12-2013
			WO	2014021957	A2	06-02-2014
WO 2010105062	A1	16-09-2010	US	2010090650	A1	15-04-2010
			US	2013271089	A1	17-10-2013
			WO	2010105062	A1	16-09-2010