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(54) **ACTIVE BATTERY MANAGEMENT METHOD**

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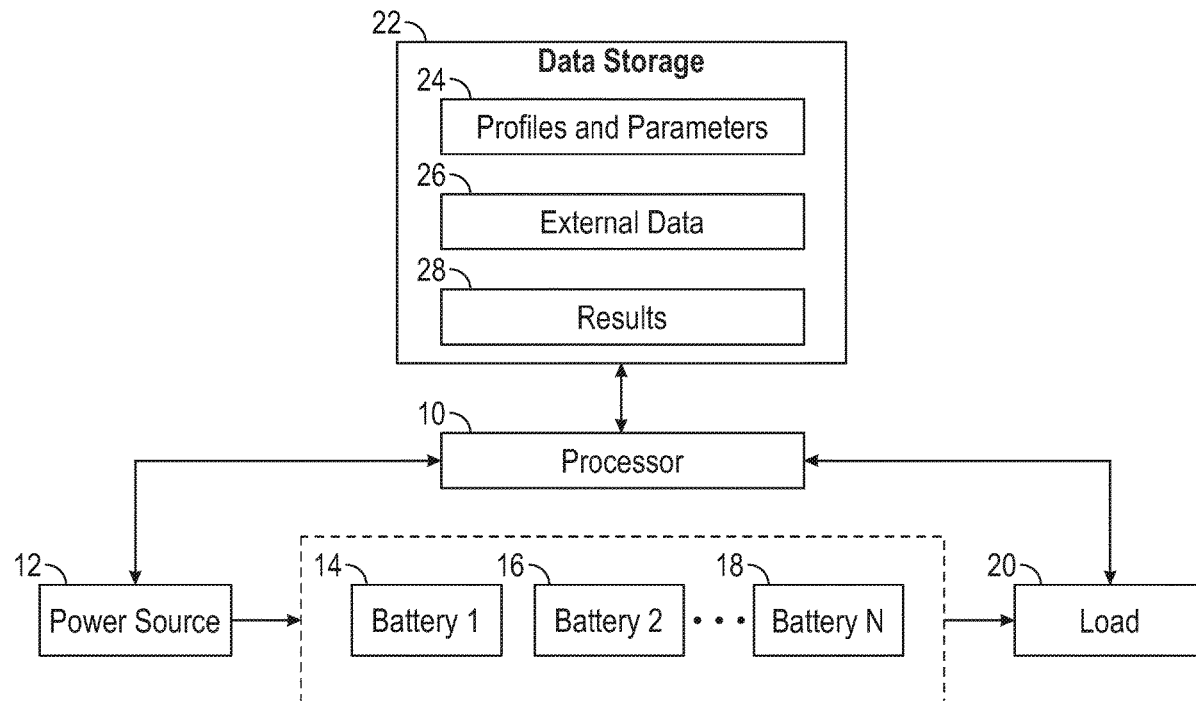
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(57)

**ABSTRACT**

Method for active battery management to optimize battery performance. The method includes providing signal injections for charging and discharging of a battery. The signal injections include various charging and discharging profiles, rates, and endpoints. Response signals corresponding with the signal injections are received, and a utility of those signals is measured. Based upon the utility of the response signals, data relating to charging and discharging of the battery is modified to optimize battery performance.



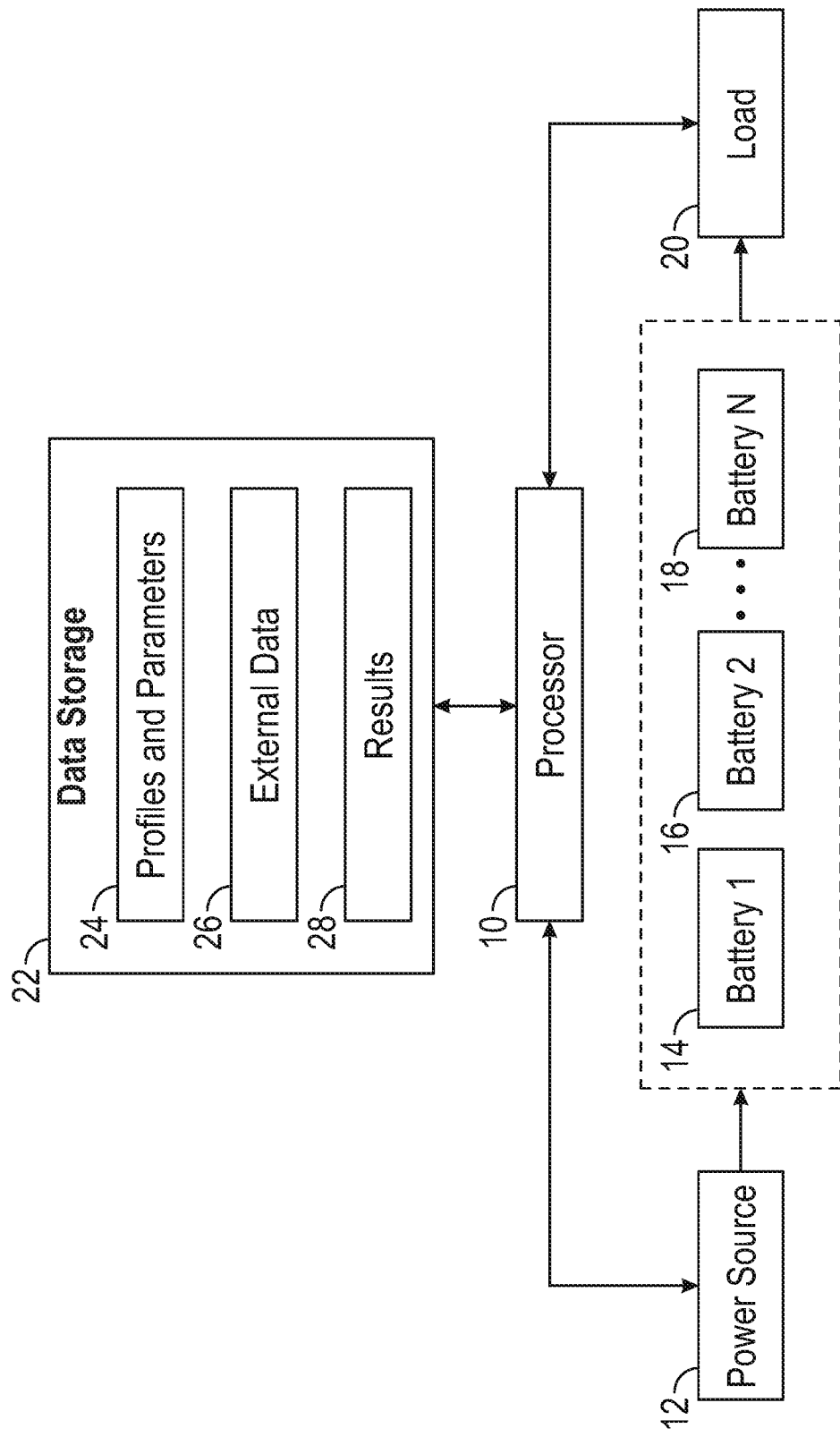


FIG. 1

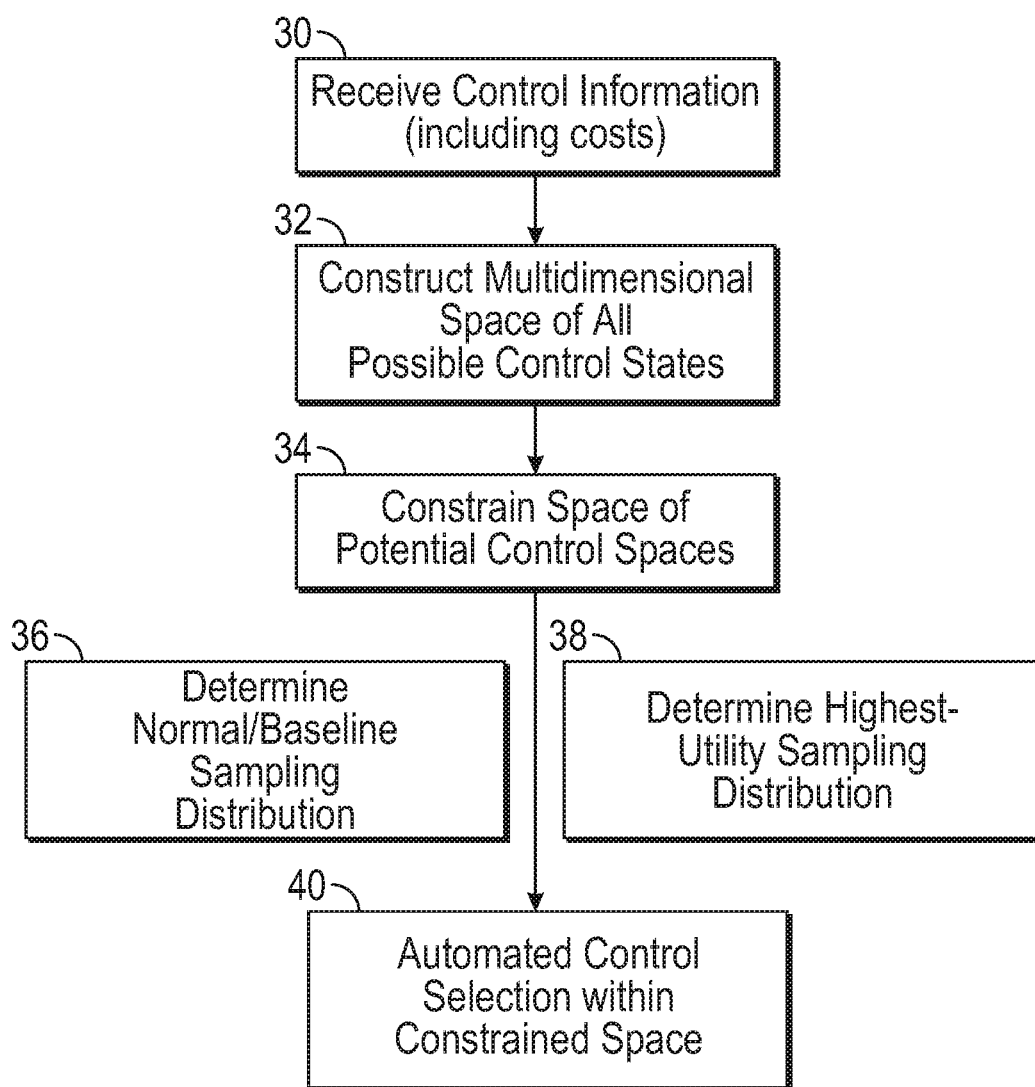


FIG. 2

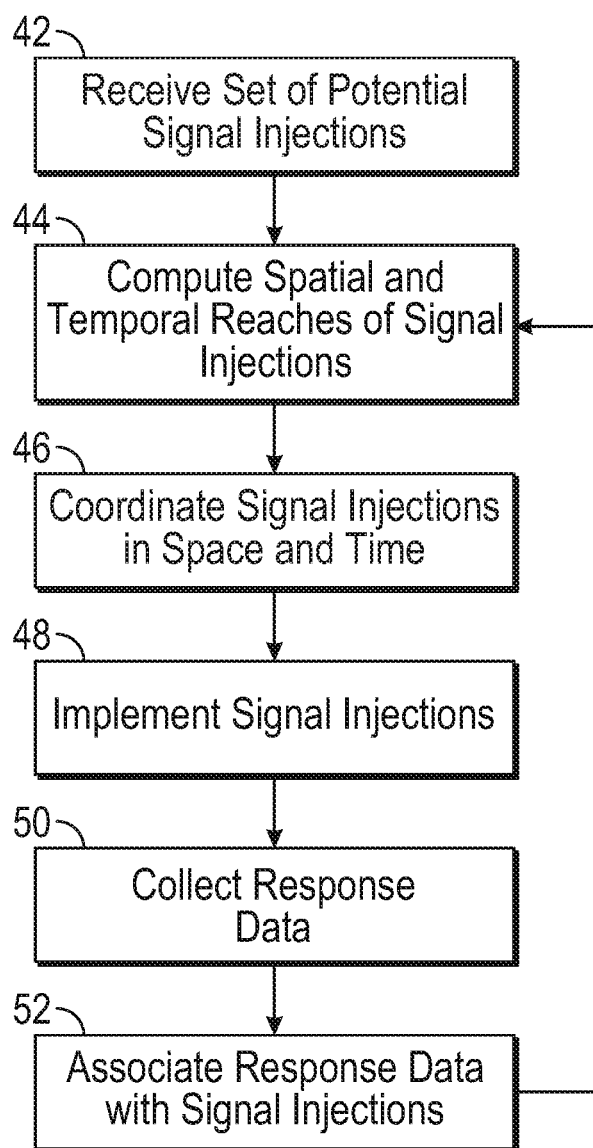


FIG. 3

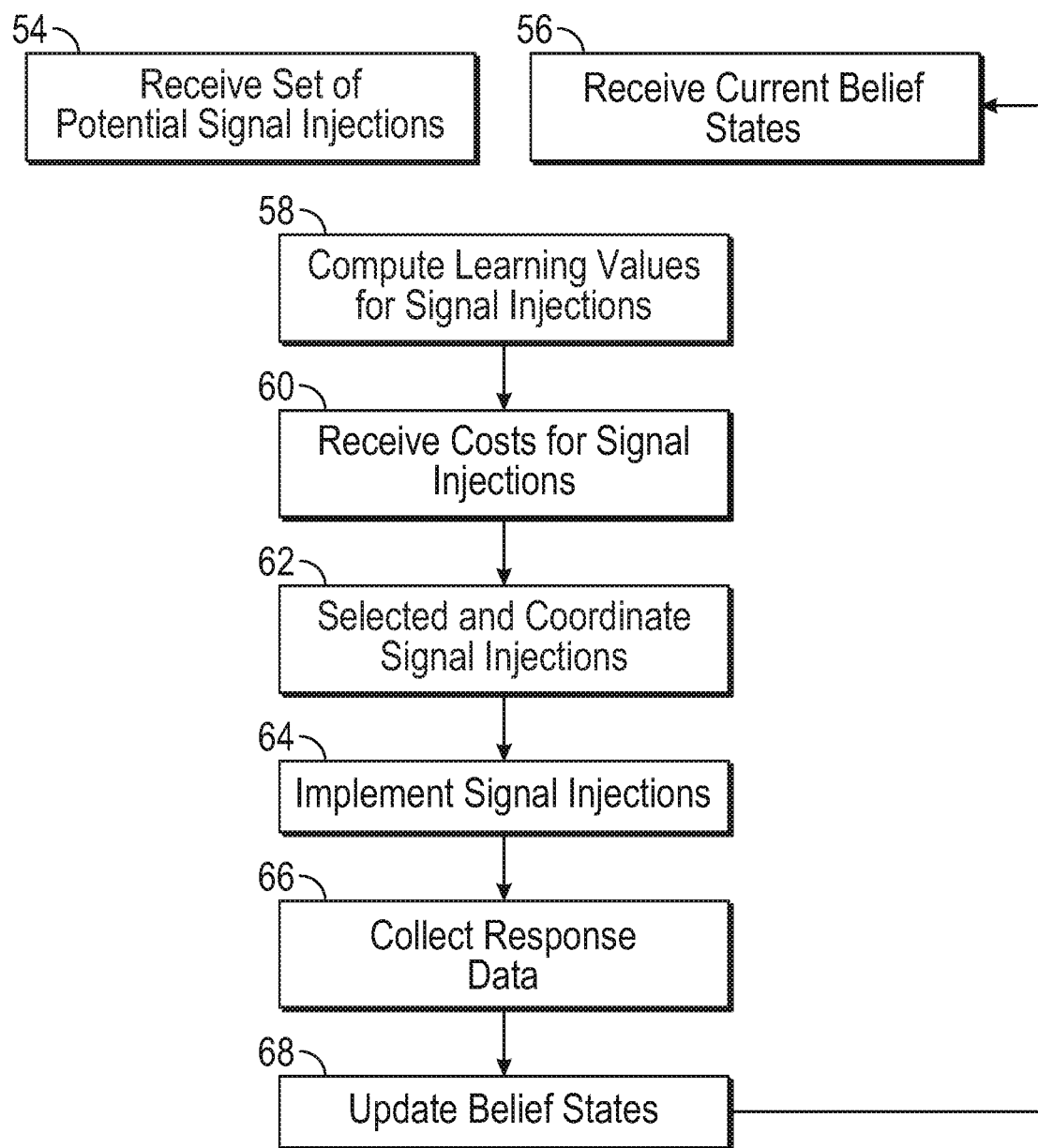


FIG. 4

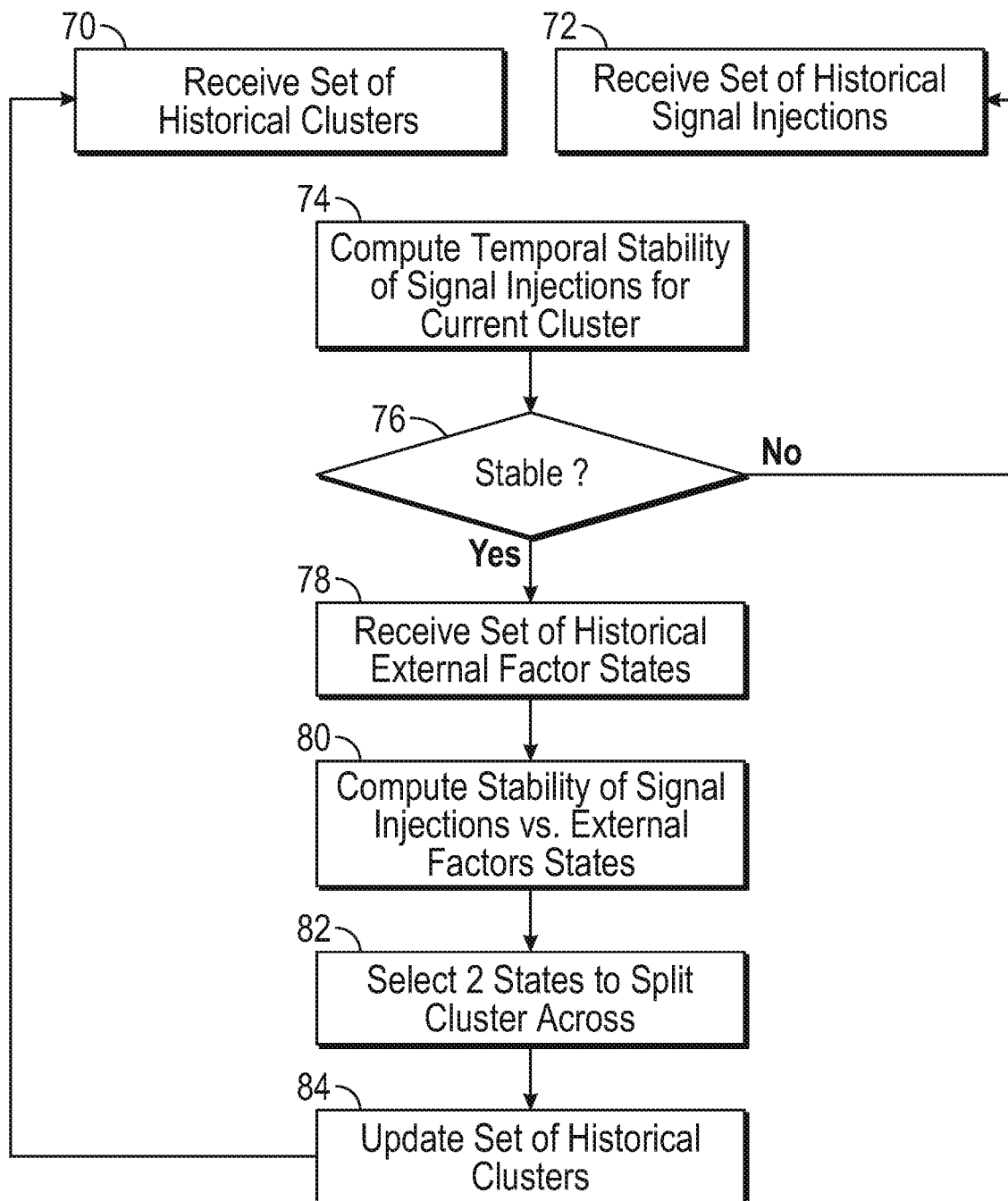
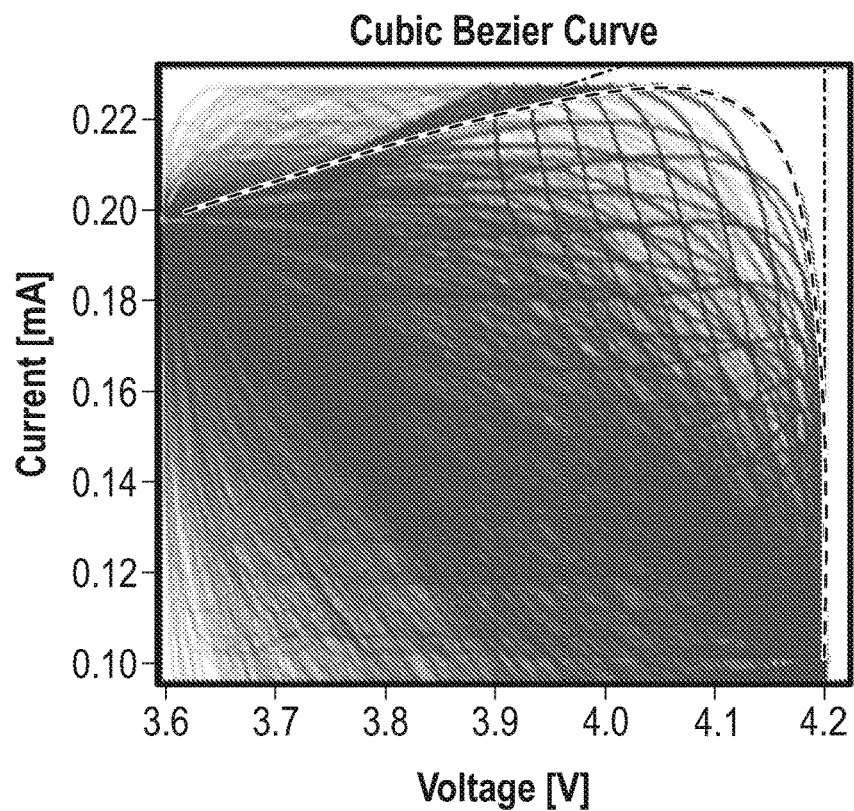
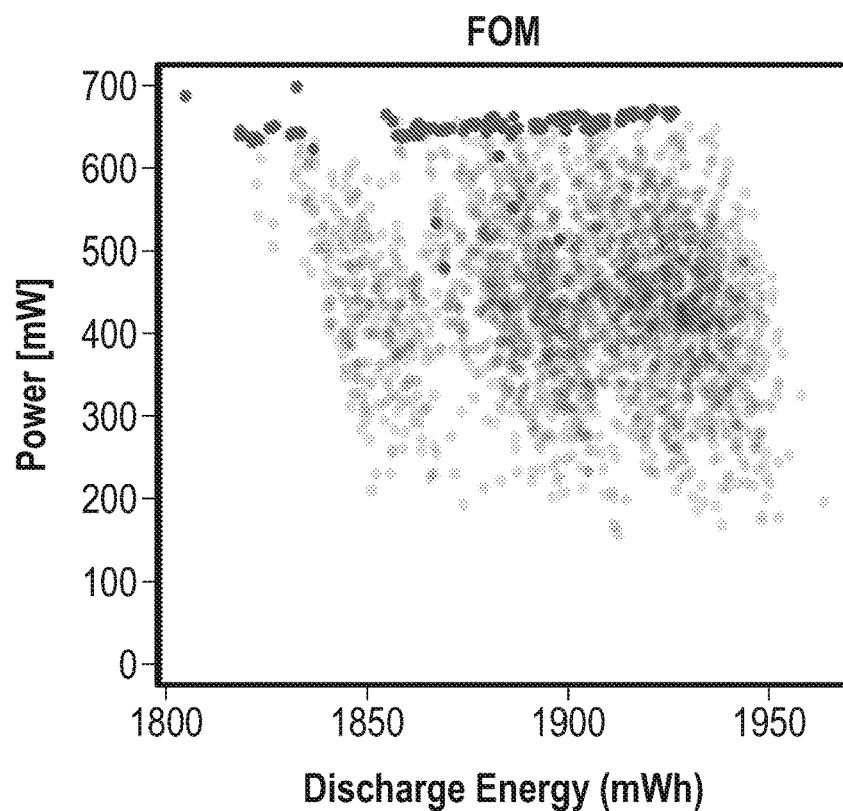
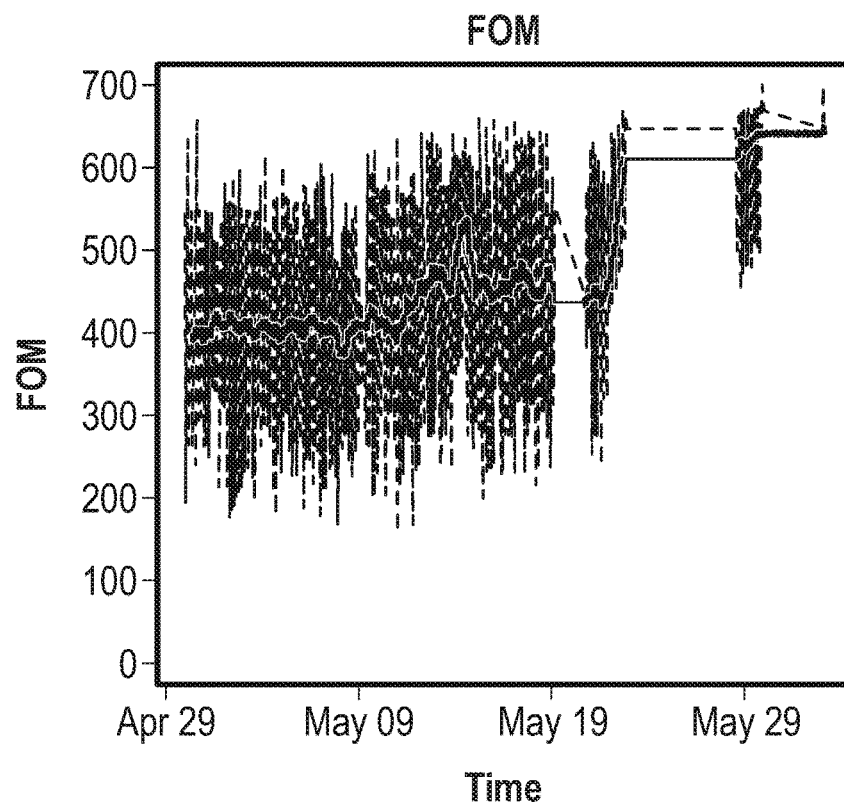
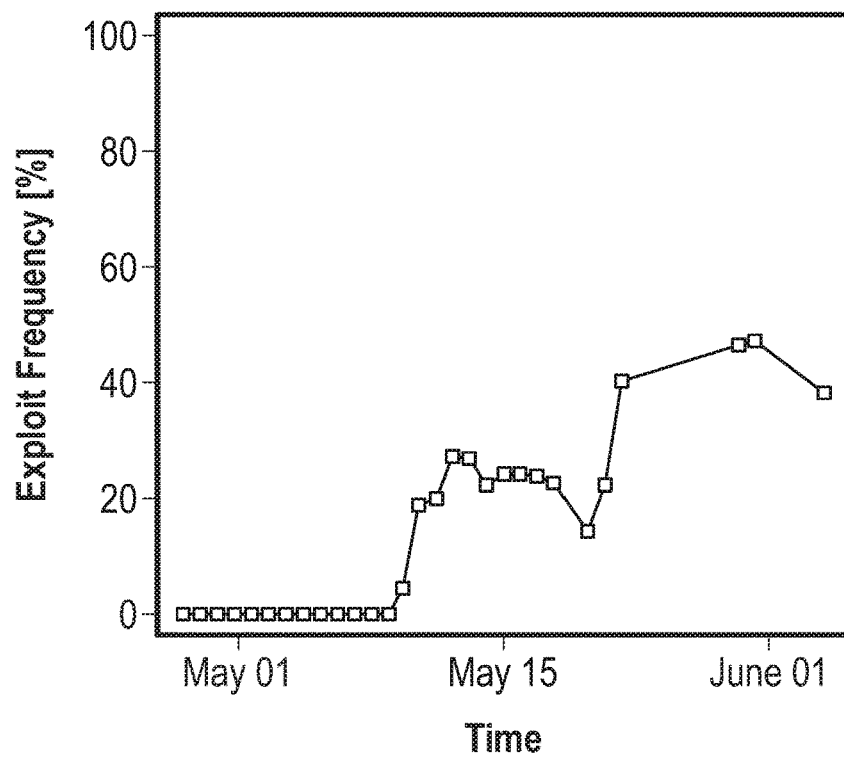


FIG. 5

**FIG. 6A****FIG. 6B**



**FIG. 6C**



**FIG. 6D**

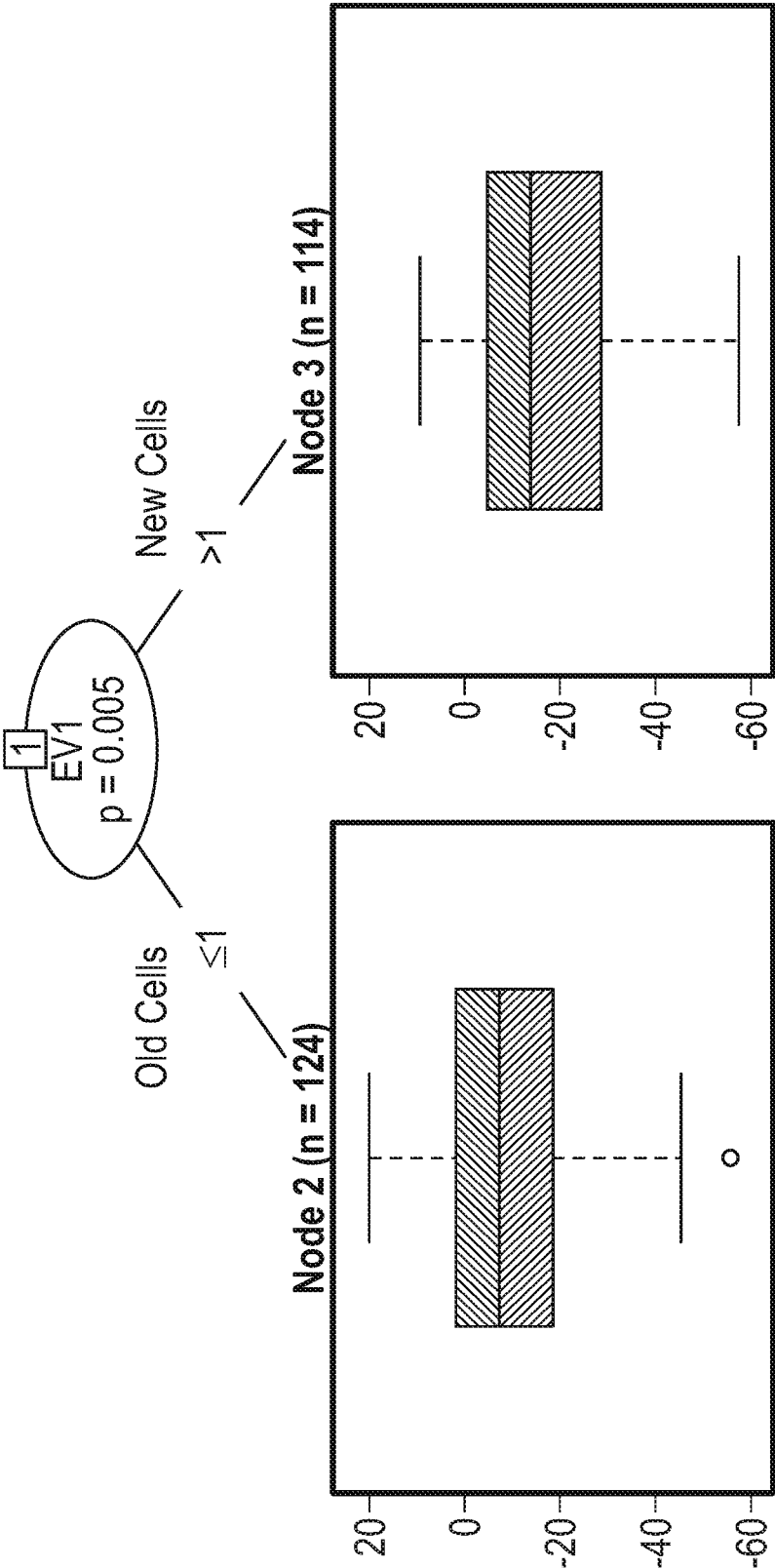


FIG. 7A

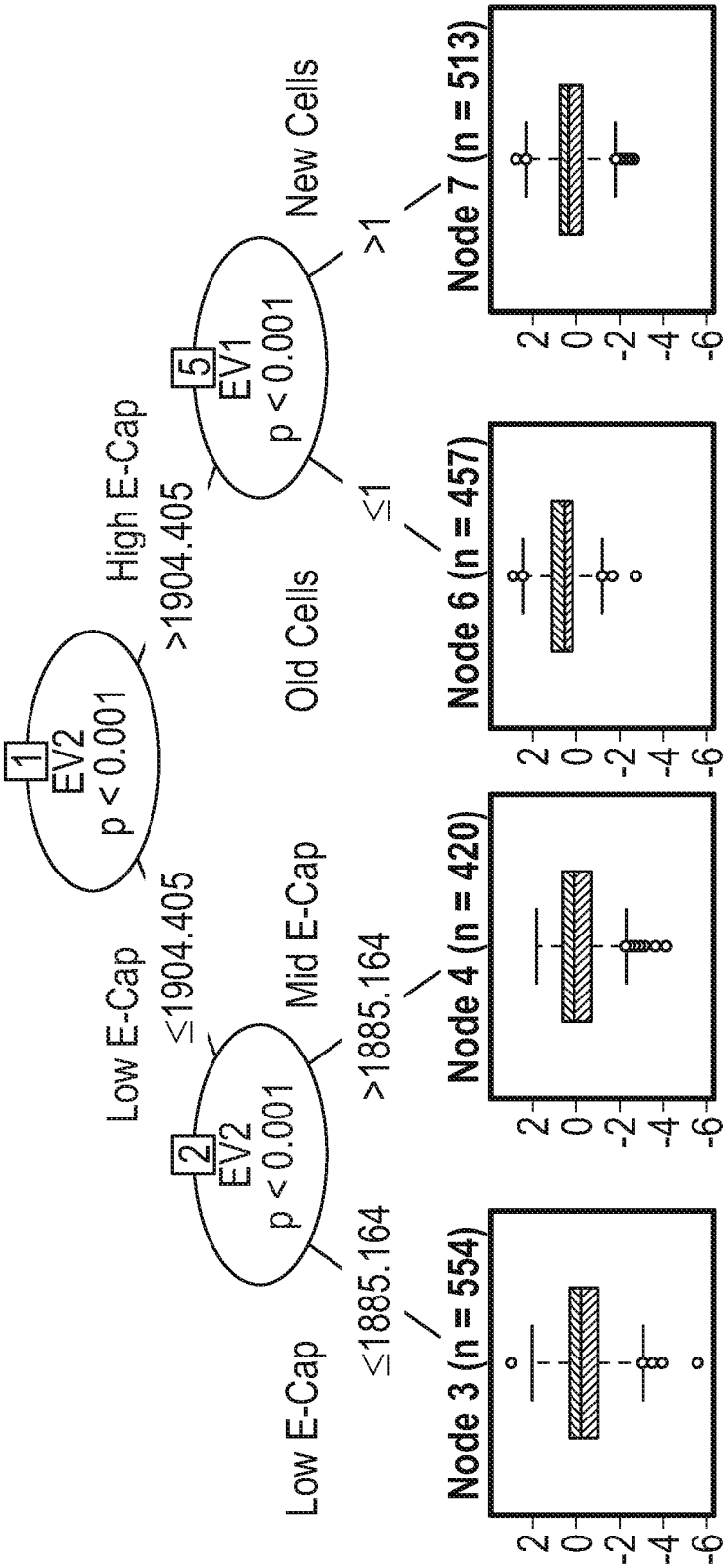


FIG. 7B

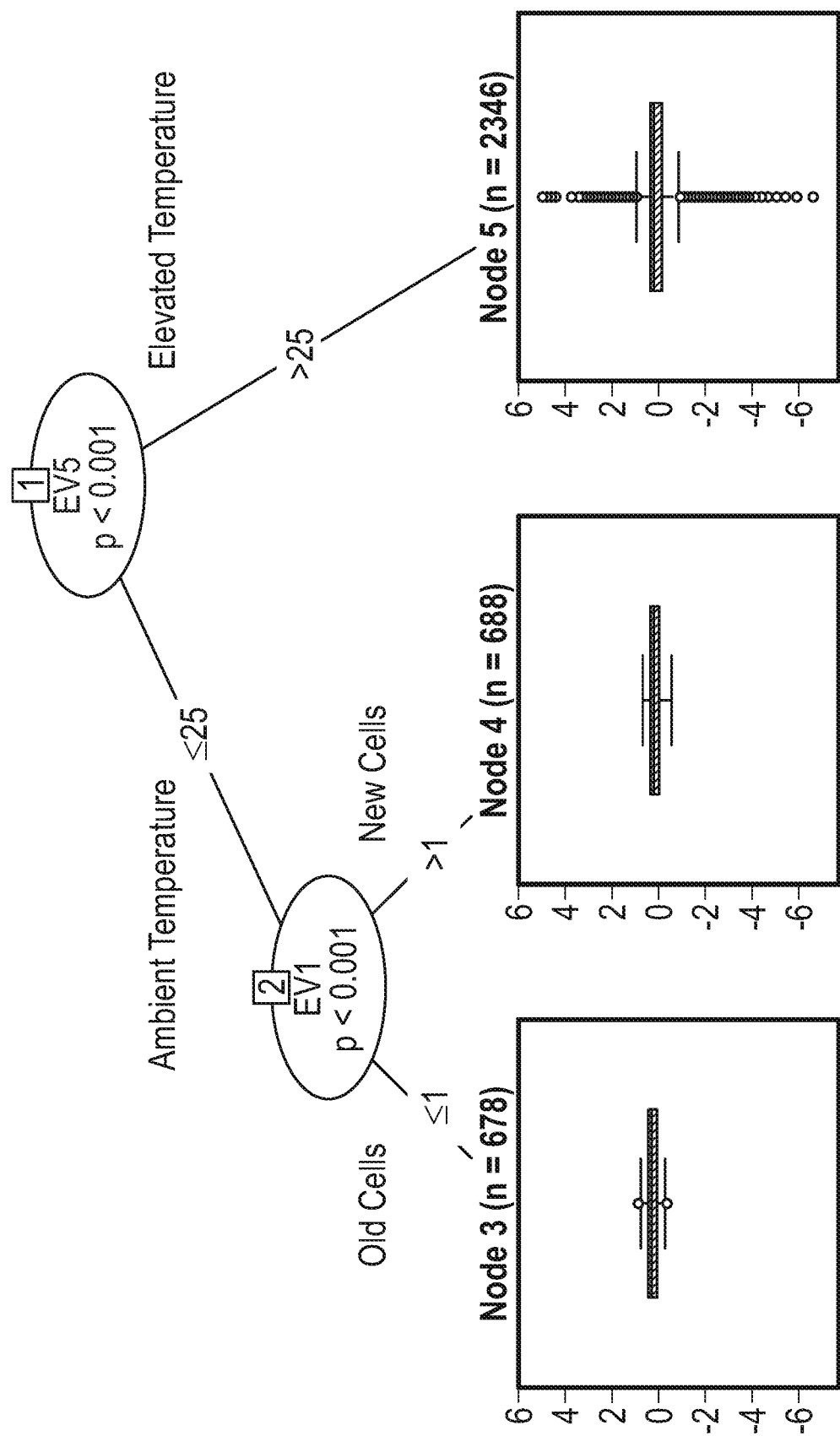


FIG. 7C

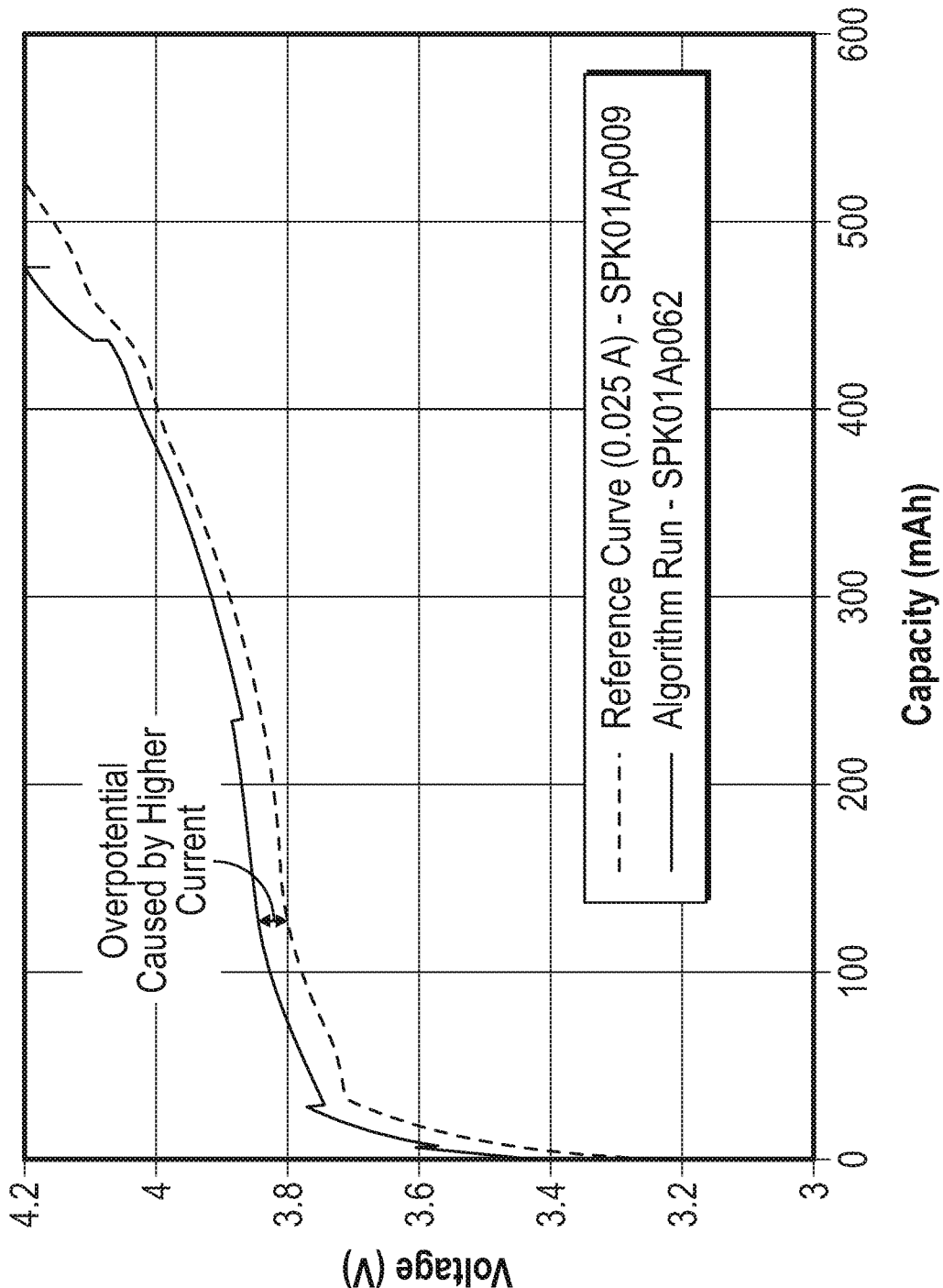


FIG. 8A

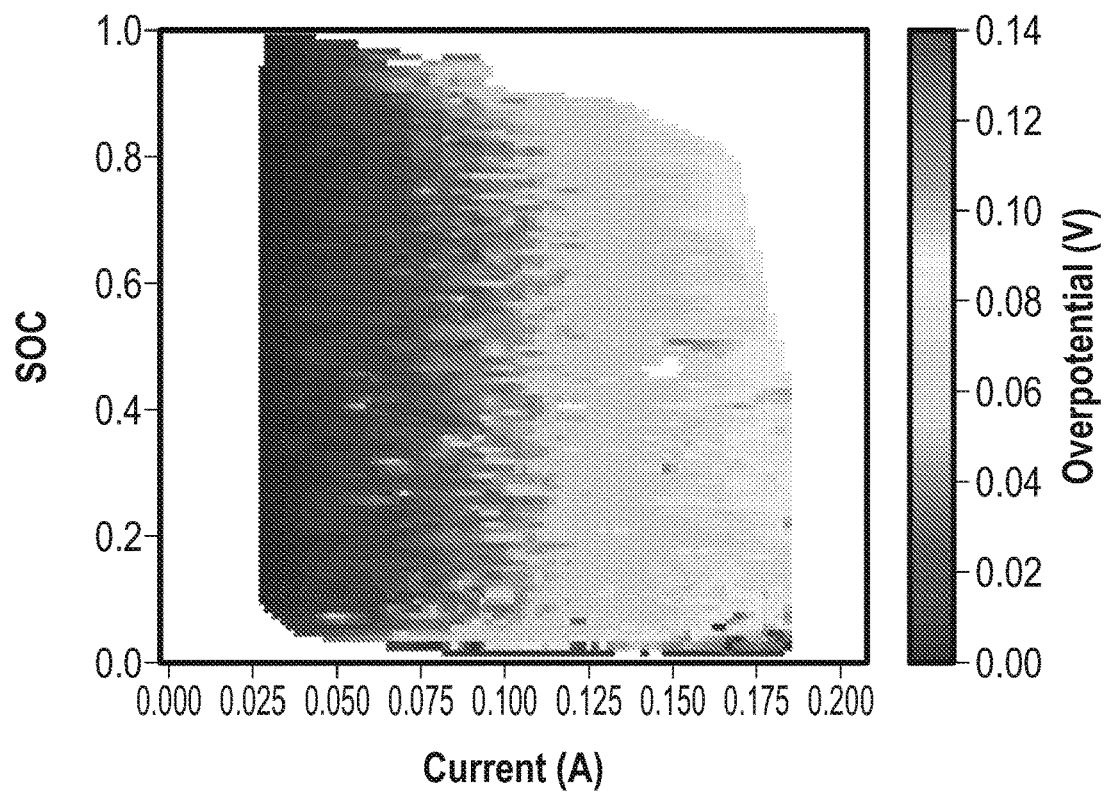


FIG. 8B

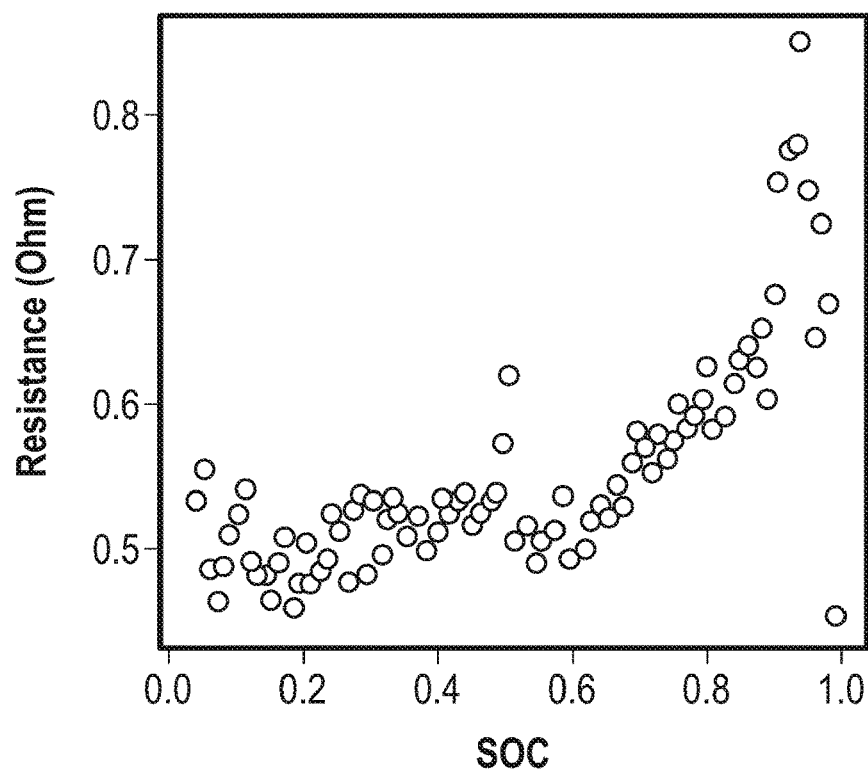


FIG. 8C

## ACTIVE BATTERY MANAGEMENT METHOD

### BACKGROUND

**[0001]** Battery management is of critical importance to a number of commercial applications ranging from consumer electronics to automotive electrification and grid-level energy storage. Battery management is also a key component of the value proposition of any battery system whose utility depends on delivering a minimum amount of energy reliably and safely over an extended period of time, from a couple of years for consumer electronics to a decade for grid installations.

### SUMMARY

**[0002]** A first method for active battery management includes injecting randomized controlled signals in charging or discharging of a battery and ensuring the signal injections occur within normal operational ranges and constraints. The method also includes monitoring performance of the battery in response to the controlled signals, computing confidence intervals about the causal relationships between the battery performance and the controlled signals, and selecting optimal signals for the charging or discharging of the battery based on the computed confidence intervals.

**[0003]** A second method for active battery management includes providing signal injections for charging or discharging of a battery and receiving response signals corresponding with the signal injections. The method also includes measuring a utility of the response signals, accessing data relating to charging or discharging of the battery, and modifying the data based upon the utility of the response signals.

### BRIEF DESCRIPTION OF THE DRAWINGS

**[0004]** The accompanying drawings are incorporated in and constitute a part of this specification and, together with the description, explain the advantages and principles of the invention. In the drawings,

**[0005]** FIG. 1 is a diagram illustrating a system for implementing an active battery management method;

**[0006]** FIG. 2 is a flow chart of a search space method for the system;

**[0007]** FIG. 3 is a flow chart of a signal injection method for the system;

**[0008]** FIG. 4 is a flow chart of a continuous learning method for the system;

**[0009]** FIG. 5 is a flow chart of a memory management method for the system;

**[0010]** FIGS. 6A-6D illustrate the search space of all possible charge profiles for the Examples;

**[0011]** FIGS. 7A-7C illustrate that the algorithm in the Examples identified distinct effect sizes for old cells versus new cells; and

**[0012]** FIGS. 8A-8C illustrate voltage versus capacity for a charge profile assigned by the algorithm in the Examples.

### DETAILED DESCRIPTION

**[0013]** Embodiments of the invention include a method for improving battery management by implementing random experiments on the charge and discharge variables and inferring their causal effects on utility metrics such as energy capacity, power, fade rate, charge time, internal resistance,

state of health, cell imbalance, temperature, cell swelling, electricity cost, and more. Linear combinations of any of the above utility metrics may also be defined to give the figure of merit which balances competing requirements. This battery management can be used in, for example, electric or hybrid vehicles, electric bicycles, consumer electronic devices, grid storage systems and other vehicles and devices using batteries.

**[0014]** FIG. 1 is a diagram illustrating a system for implementing an active battery management method. The system includes a processor 10 electrically coupled with a power source 12, a load 20, and a data storage 22. Power source 12 provides power for charging one or more batteries 14, 16, and 18, and the batteries provide power to load 20. Data storage 22, such as an electronic memory, stores profiles and parameters 24, external data 26, and results 28. Results can include, for example, time series of current and voltage, energy capacity, temperature and more for each cell or string of cells.

**[0015]** In use, processor 10 injects signals to power source 12 using profiles and parameters 24 and possibly external data 26 in order to evaluate the performance of batteries 14, 16, and 18, for example how the batteries perform for charging and discharging of them. Performance metrics can include, for example, delivered power, energy capacity, and fade rate. Processor 10 stores as results 28 the response to the signal injections, and those responses can be used to optimize performance of the batteries. The processing for the battery management can occur locally with dedicated firmware on the battery charging system, on standalone PC, or be cloud based and occur remotely from the batteries.

**[0016]** Profiles and parameters 24 includes possible charging and discharging rates, charging and discharging profiles, and profile endpoints. The charging and discharging profiles include the shape of such profiles and possibly time at a particular state of charge or voltage. The charging endpoints include the percentage of charge in the batteries at which to start and stop charging the batteries, and the discharging endpoints include the percentage of charge in the batteries at which to start and stop discharging the batteries. The profiles and parameters can be stored in look-up tables, for example. External data 26 can include, for example, environmental conditions or factors such as temperature, humidity, airflow around the batteries, time of day or year, and time since turning on the device or vehicle using the batteries. Also, active cooling or heating of the batteries can be used as other control variables with parameters of temperature set points, rates, and gradients in time and space. In the case of portable electronic devices, external data can also include the following with respect to such devices: usage of applications, user settings, a scheduled event or alarm, a power consumption pattern, a time of day, or the location of the device. Similarly in the case of an electrical vehicle, external data can include time of day or time next scheduled use, typical driving patterns for the vehicle, electricity cost versus time (i.e., for example to avoid peak pricing), predicted weather conditions, planned travel route, or traffic conditions.

**[0017]** The batteries can include a single physical battery or multiple physical batteries that collectively provide power. In the case of multiple physical batteries, the batteries may have the same or different construction or electrochemistry. The process of injecting signals for charging and discharging of the batteries seeks to optimize charging and

discharging profiles for a particular battery or a pack of batteries. The pack of batteries can be considered as a single battery where the pack collectively operates together, or the pack of batteries can be considered multiple physical batteries driven one-by-one. Examples of types of batteries include lithium ion, reflow, lead acid, and others.

**[0018]** FIGS. 2-5 are flow charts of methods for active battery management to optimize charging and discharging profiles and parameters. These methods can be implemented in, for example, software modules for execution by processor 10.

**[0019]** FIG. 2 is a flow chart of a search space method. The search space method includes the following steps: receive control information (including costs) 30; construct multidimensional space of all possible control states 32; constrain space of potential control spaces 34; determine normal/baseline sampling distribution 36; determine highest utility sampling distribution 38; and automated control selection within constrained space 40.

**[0020]** FIG. 3 is a flow chart of a signal injection method. The signal injection method includes the following steps: receive set of potential signal injections 42; compute spatial and temporal reaches of signal injections 44; coordinate signal injections in space and time 46; implement signal injections 48; collect response data 50; and associate response data with signal injections 52.

**[0021]** The signal injections are changes in charging and discharging profiles and parameters for battery management. The responses to signal injection are typically battery performance resulting from or related to the changes in profiles and parameters from the signal injections. For example, the algorithm can perturb values in a look-up table representing charging and discharging profiles and parameters, and then monitor and store the corresponding battery performance response. The temporal and spatial reaches of signal injections relate to, respectively, when and where to measure the response signals to those signal injections that are used for computing causal relationships. The cost of signal injection typically relates to how the signal injection affects battery performance, for example signal injection can result in lower battery performance, and is controlled by the specified experimental range. The queue for signal injection involves the order and priority of signal injections and relies on blocking and randomization to guarantee high internal validity at all times, even when optimizing utility. The utility of responses to signal injection involves the effectiveness of the signal injections or other measures of utility.

**[0022]** FIG. 4 is a flow chart of a continuous learning method. The continuous learning method includes the following steps: receive set of potential signal injections 54; receive current belief states 56; compute learning values for signal injections 58; receive costs for signal injections 60; select and coordinate signal injections 62; implement signal injections 64; collect response data 66; and update belief states 68.

**[0023]** The belief states are a set of different models of battery performance in response to charging and discharging. These belief states may have attached uncertainty values reflecting the likelihood that they are accurate given the current set of trials and knowledge that may tend to confirm or falsify these different models, and the information that can further confirm or falsify the models may be included in this data or derived from the basic characteristics of the particular model and the physics of the underlying system.

**[0024]** The learning value is a measure of the value that knowledge generated as a result of the signal injection may provide to subsequent decision-making by a system, such as determining that a particular charging or discharging profile is more likely to be optimal.

**[0025]** In the sense of a multi-objective optimization, this can include complex trade-offs between operational goals (e.g., performance versus range) and where optimality may vary over time. The learning value may be computed through, for example, predicting the raw number of belief states that may be falsified according to the predictions of a Partially Observable Markov Decision Process (POMDP) or other statistical model, predicted impacts of the signal injection on the uncertainty levels in the belief states in such models, or experimental power analyses computing the reduction in uncertainty and narrowing of confidence intervals based on increasing to the current sample size.

**[0026]** FIG. 5 is a flow chart of a memory management method. The memory management method includes the following steps: receive set of historical clusters 70;

**[0027]** receive set of historical signal injections 72; and compute temporal stability of signal injections for current clusters 74. If the signal injections from step 74 are stable 76, then the memory management method executes the following steps: receive set of historical external factor states 78; compute stability of signal injections versus external factors states 80; select two states to split cluster across 82 only if there is enough variance across the two states and enough data within each state (after splitting) to be able to drive decisions in each state (i.e., compute confidence intervals); and update set of historical clusters 84.

**[0028]** A cluster is a group of experimental units that are statistically equivalent with respect to the measure causal effects. Within a cluster, effects are measured free of bias and/or confounding effects from external factors, which guarantees that we are measuring causation and not just correlations/associations. Distribution of measured effects within each cluster are approximately normally distributed.

**[0029]** Table 1 provides an algorithm of an embodiment for automatically generating and applying causal knowledge for active battery management. This algorithm can be implemented in software or firmware for execution by processor 10.

TABLE 1

|   |                                                                                                                                                           |
|---|-----------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1 | inject randomized controlled signals into battery charging and discharging based upon changes in charging and discharging profiles and related parameters |
| 2 | ensure signal injections occur within normal operational ranges and constraints                                                                           |
| 3 | monitor battery performance in response to the signal injections                                                                                          |
| 4 | compute causal knowledge about the relationship between signal injections and monitored battery performance                                               |
| 5 | select optimal signals for the battery performance based on current causalknowledge and possibly external data                                            |

## EXAMPLES

### Method for Maximizing Delivered Power

**[0030]** Power characterizes the amount of energy per unit time. Maximizing power is a balancing act of minimizing charge time while minimizing the loss in energy capacity with each cycle. In electric vehicle applications, increased

power enables faster acceleration and greater performance. In grid applications such as peak shaving where a typical charge/discharge cycle is 24 hours, increased power translates to longer life-time and/or smaller installations.

**[0031]** In this example, we conducted the following experiment: 32 cells were connected to a Maccor cycler (see Reference section for details) with 16 cells partially aged (N cycles/cell on average) and 16 cells brand new (0 cycle/cell). The search space consisted of a family of spline curves defined as cubic Bezier functions (see Reference for definition) that specified the charge profile for each cell. For implementation purposes, these charge curves were discretized into 5 constant-current charge steps. The start point (constant current at 200 mA up to 3.6V) and end point (constant current at 100 mA up to 4.2V) were both fixed; an additional constant voltage step was added at the end of the charge profile ( $V=4.2V$ , cutoff current=25 mA) to ensure that each cell reached its full capacity, as commonly done in practice. The 4 independent variables consisted of the two coordinates (cutoff voltage: V, and constant current: I) of the two control points of the cubic Bezier function. Each independent variable was discretized into 8 levels, resulting in a total of 4096 possible combinations. Once fully charged, the cells were discharged under a fixed discharge profile (constant current at 250 mA to 3V).

**[0032]** We focused on the charge profile primarily for the purpose of illustration and simplicity, and the disclosed method can be expanded to the discharge profile as well as any other variable relevant to cell cycling. The Figure Of Merit (FOM) was defined as delivered power calculated as the discharge energy divided by cycle time (i.e., charge time+discharge time). Prior to any significant aging of the cells, both discharge energy and discharge time were nearly constant across cells (or cycles) and the FOM was driven primarily by charge time. Additional dependent variables were recorded with each cycle including charge energy and charge time. External variables were also recorded with each cycle to explore their possible effect of the dependent variables and find clustering opportunities. The external variables included cell identification (ID), old versus new cell, discharge energy and discharge time.

**[0033]** Data was recorded over weeks. During the initial explore phase, the algorithm assigned charge profiles randomly across the search space and built confidence intervals (CIs) around the expected causal effect of each IV level on the FOM. Once some of the CIs were significantly distinct and non-overlapping, which occurred after exploring ~30% of the total search space, the algorithm started exploiting that knowledge by assigning more frequently levels with the highest utility, resulting in a gradual increase in the FOM. The algorithm also started identifying clusters across which causal effects were statistically different. While the optimum levels may not change across clusters, their relative effects did change due to differential ageing and differential initial state of health.

**[0034]** FIGS. 6A-6D show the search space of all possible charge profiles for the described experiment. In FIG. 6A, the optimum charge profile is shown as the dashed line with its end points and control handle points shown as the dot-dashed line. The chosen FOM (total delivered power) is plotted versus discharge energy. The power values associated with the optimum charge profile are shown as the dark gray circles. The FOM and the exploit frequency are also plotted as a function of time. FIG. 6A shows the search space

of all possible charge profiles. FIG. 6B shows the FOM versus discharge energy. FIG. 6C shows the FOM versus time. FIG. 6D shows the exploit frequency.

**[0035]** FIGS. 7A-7C show that, over time, the algorithm identified distinct effect sizes for old cells versus new cells. Once clustering is initiated, the algorithm exploits charge profiles that are optimum for each distinct cluster, which may or may not be the same across clusters. FIGS. 7A and 7B illustrate the Example of method for maximizing delivered power, where E-Cap refers to energy capacity. FIG. 7C illustrates the Example of method for maximizing delivered power under environmental conditions.

#### Method for Measuring Cell Internal Resistance

**[0036]** Data from the previous experiment was also analyzed to characterize the internal resistance of the cells during each cycle and over time. Mapping the internal resistance as a function of current and state of charge (SOC) can typically be accomplished by performing complete cycles at various rates. This analysis is time consuming and, furthermore, only represents the internal resistance at the beginning of the life of the cell.

**[0037]** This analysis can also be inaccurate because the results of once cycle are not independent of the previous cycle. By randomizing with the algorithm disclosed herein, this effect is mitigated.

**[0038]** Here, data from each actual cycle was used to estimate internal resistance in the following way: for each constant-current step, the internal resistance value was approximated by  $R=\Delta V/\Delta I$ , where  $\Delta V$  was the change in average potential compared to a reference cell cycled at 25 mA and  $\Delta I$  was the current difference compared to the reference cell. R was estimated for each cell, each cycle and each of the 5 constant-current steps. A nearly continuous curve of internal resistance versus state of charge was obtained, illustrating the expected behavior of Li-ion batteries. These results are shown in FIGS. 8A-8C.

**[0039]** FIG. 8A shows voltage versus capacity for a charge profile assigned by the algorithm (solid line) versus reference C/20 charge profile (dashed line) illustrating the overpotential  $\Delta V$ . FIG. 8B shows SOC and overpotential versus current. FIG. 8C shows internal resistance versus SOC.

**[0040]** Knowledge of in situ internal resistance over time can be used to improve the performance and safety of the battery management system by eliminating charge profiles in the search space that could lead to significant over- and under-voltage, heating and degradation of the cells. Internal resistance maps can be built from subgroups within the data, and examples of possible subgroups include but are not limited to: cell age, number of cycles, temperature exposure, cumulative discharged energy, average discharge current, average charge current, maximum charge current, average voltage, manufacturing batch. Changes in internal resistance can also be used to detect anomalous conditions such as onset of a short circuit in a battery pack.

#### Method for Balancing Cells in a Pack

**[0041]** Beyond maximizing power, causal knowledge of the effects of charge profile variables on cell power can also be used to optimize other utility metrics, such as balancing state of health (SOH) or internal resistance across cells. While cell aging tends to be fairly uniform at the beginning of battery life (within manufacturing tolerances), it becomes

increasingly more heterogeneous and unpredictable with each additional charge/discharge cycle. This is an important consideration when repackaging used cells into packs for new applications as a way to extend their life time in less demanding applications. One example is reusing EV batteries for grid-level energy storage. The development of smart battery management systems that are capable of balancing cell ageing is critical to ensure safe, reliable and durable operations and make the application economically viable. Accurate determination of the internal resistance of each cell as well as clustering across homogeneous cell groups is an effective mechanism to quantitatively implement cell balancing in practice.

[0042] Similarly, hybrid vehicles can use systems that combine different types of cells with different performance and ageing characteristics. The power grid can use systems that combine high power and high energy storage. This translates to greater variance in the data, resulting in greater difficulty to apply standard data analytics techniques for battery management. The algorithm disclosed herein can address this type of problem by automatically identifying the minimum set of homogeneous clusters that can be used for reliable causal inference over time. The algorithm disclosed herein can also be used to implement experiments on batteries across different vehicles.

[0043] Method for Maximizing Delivered Power Under Different Environmental Conditions

[0044] In many applications, batteries are exposed to different environmental conditions due to weather, infrequent operations, and more. For the purpose of illustration, we focused on ambient temperature as an external factor, which is common to many applications and has a large known effect of cell performance. We conducted a second set of experiments with 8 cells placed in an oven under elevated ambient temperature of 45° C. The results showed how the optimum charge profile varies with environmental conditions

#### References for the Examples

[0045] Cells: Rechargeable Li-ion polymer battery wound pouch cells, 5.0x30x35 mm, nominal capacity 500 mAh; graphite anode and LiCoO<sub>2</sub> cathode (E-Group, Mt. Laurel, N.J.).

[0046] Maccor: 96 channel, Series 4000 Maccor (Tulsa, Okla.).

[0047] Cubic Bezier function:

[0048] Four points  $P_0$ ,  $P_1$ ,  $P_2$  and  $P_3$  in the plane or in higher-dimensional space define a cubic Bezier curve. The curve starts at  $P_0$  going toward  $P_1$  and arrives at  $P_3$  coming from the direction of  $P_2$ . Usually, the curve will not pass through  $P_1$  or  $P_2$ ; these points are only there to provide directional information. The distance between  $P_1$  and  $P_2$  determines “how far” and “how fast” the curve moves toward  $P_1$  before turning toward  $P_2$ .

[0049] Writing  $B_{P_i, P_j, P_k}(t)$  for the quadratic Bezier curve defined by  $P_i$ ,  $P_j$ , and  $P_k$ , the cubic Bezier curve can be defined as an affine combination of two quadratic Bezier curves:

$$B(t) = (1-t)B_{P_0, P_1, P_2}(t) + tB_{P_1, P_2, P_3}(t), \quad 0 \leq t \leq 1$$

[0050] The explicit form of the curve is:

$$B(t) = (1-t)^3 P_0 + 3(1-t)^2 t P_1 + 3(1-t)t^2 P_2 + t^3 P_3, \quad 0 \leq t \leq 1$$

[0051] For some choices of  $P_i$  and  $P_2$  the curve may intersect itself or contain a cusp.

1. A method for active battery management, comprising steps of:

- injecting randomized controlled signals in charging or discharging of a battery;
- ensuring the signal injections occur within normal operational ranges and constraints;
- monitoring performance of the battery in response to the controlled signals;
- computing confidence intervals about the causal relationships between the battery performance and the controlled signals; and
- selecting optimal signals for the charging or discharging of the battery based on the computed confidence intervals.

2. The method of claim 1, wherein the controlled signals comprise a charging profile or a discharging profile.

3. The method of claim 1, wherein the controlled signals comprise a charging rate or a discharging rate.

4. The method of claim 1, wherein the controlled signals comprise charging profile endpoints or discharging profile endpoints.

5. The method of claim 1, wherein the normal operational ranges comprise a multidimensional space of possible control states generated based on control information and operational constraints.

6. The method of claim 1, wherein the selecting step further comprises selecting the optimal signals based upon external data comprising environmental conditions.

7. The method of claim 6, wherein the environmental conditions comprise at least one of a temperature, a humidity, or an airflow around the battery.

8. The method of claim 1, wherein the selecting step further comprises selecting the optimal signals based upon external data comprising at least one of, with respect to a portable electronic device, usage of applications, user settings, a scheduled event or alarm, a power consumption pattern, a time of day, or a location of the device.

9. The method of claim 1, wherein the battery comprises a pack of batteries.

10. A method for active battery management, comprising steps of:

- providing signal injections for charging or discharging of a battery;
- receiving response signals corresponding with the signal injections;
- measuring a utility of the response signals;
- accessing data relating to charging or discharging of the battery; and
- modifying the data based upon the utility of the response signals.

11. The method of claim 10, wherein the signal injections comprise a charging profile or a discharging profile.

12. The method of claim 10, wherein the signal injections comprise a charging rate or a discharging rate.

13. The method of claim 10, wherein the signal injections comprise charging profile endpoints or discharging profile endpoints.

14. The method of claim 10, wherein the accessing step comprises accessing a look-up table.

15. The method of claim 10, wherein the signal injections have a spatial reach.

**16.** The method of claim **10**, wherein the signal injections have a temporal reach.

**17.** The method of claim **10**, wherein the modifying step further comprises modifying the data based upon external data comprising environmental conditions.

**18.** The method of claim **17**, wherein the environmental conditions comprise at least one of a temperature, a humidity, or an airflow around the battery.

**19.** The method of claim **10**, wherein the selecting step further comprises selecting the optimal signals based upon external data comprising at least one of, with respect to a portable electronic device, usage of applications, user settings, a scheduled event or alarm, a power consumption pattern, a time of day, or a location of the device.

**20.** The method of claim **10**, wherein the battery comprises a pack of batteries.

\* \* \* \* \*