Data-driven and temperature-cycles based remaining useful life estimation of an electronic device

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Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

Citation (APA):
Dragicevic, T., Izquierdo, P., & Barragan Moreno, A. (2022). Data-driven and temperature-cycles based remaining useful life estimation of an electronic device. (Patent No. *WO2022248532*).

(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property Organization
International Bureau

(43) International Publication Date
01 December 2022 (01.12.2022)

WIPO | PCT

(10) International Publication Number
WO 2022/248532 A1

(51) International Patent Classification:
G01R 31/26 (2020.01) *G01R 31/392* (2019.01)

(21) International Application Number:
PCT/EP2022/064158

(22) International Filing Date:
25 May 2022 (25.05.2022)

(25) Filing Language: English

(26) Publication Language: English

(30) Priority Data:
21175710.9 25 May 2021 (25.05.2021) EP

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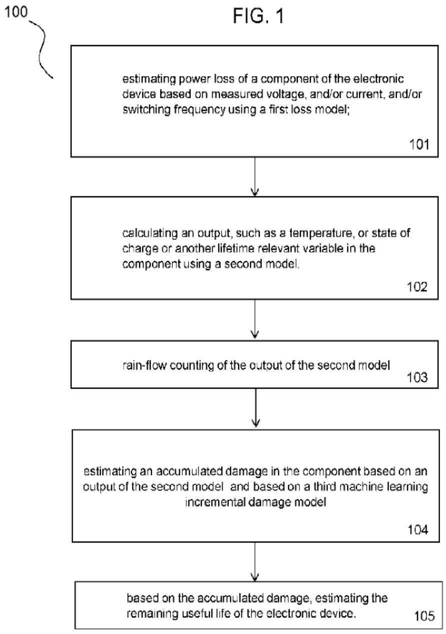
(81) Designated States *(unless otherwise indicated, for every kind of national protection available)*: AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IQ, IR, IS, IT, JM, JO, JP, KE, KG, KH, KN, KP, KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, WS, ZA, ZM, ZW.

(84) Designated States *(unless otherwise indicated, for every kind of regional protection available)*: ARIPO (BW, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SD, SL, ST, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

(54) Title: DATA-DRIVEN AND TEMPERATURE-CYCLES BASED REMAINING USEFUL LIFE ESTIMATION OF AN ELECTRONIC DEVICE

FIG. 1



(57) Abstract: A method for estimation of remaining useful life or state of health of an electronic device, such as a battery, the method comprising the steps of: estimating state of charge (SoC) of the electronic device based on measured voltage, and/or current, and/or cell temperature using a machine learning state of charge estimation model;5estimating an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, wherein the machine learning incremental damage model is trained with laboratory data and real life and/or field operation data from the electronic device itself and/or from similar electronic devices; and based on the accumulated damage, 10estimating the remaining useful life or the state of health of the electronic device.

WO 2022/248532 A1

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Declarations under Rule 4.17:
— *of inventorship (Rule 4.17(iv))*

Published:
— *with international search report (Art. 21(3))*
— *in black and white; the international application as filed contained color or greyscale and is available for download from PATENTSCOPE*

Data-driven and temperature-cycles based remaining useful life estimation of an electronic device

The disclosure relates to a method using machine learning models, optionally in combination with empirical models, to determine the remaining useful lifetime (RUL) of an electronic device based on the historical cycles of relevant lifetime variables or stress variables, such as a switch junction temperature, or solder temperature or bonding temperature, or state of charge or voltage. The disclosure further relates to a computer program implementing the method, to a computing device executing the method locally and a computing system wherein the method is executed locally but one of the involved machine learning models is trained remotely.

Background

A huge amount of the electrical energy in the world is used for pumps, fans and compressors and similar devices. Many of these devices are powered by electronic devices, such as power electronic devices, for example power converters or power semiconductor switches. For other applications electronic devices, such as capacitors and batteries, are used.

In addition, the recent focus on green solutions on a greater scale, which will help for the sustainable transformation to limit climate change, is increasing the demand for electronic devices. Electronic devices are also widely used in the field of Internet of things (IoT) devices.

Electronic devices for powering different applications are therefore ubiquitous and, for a specific application, millions of electronic devices may be used.

Reliability issues for these millions of electronic devices are a problem and, for predictive maintenance and avoidance of potential catastrophic failure, it is crucial to reliably estimate the remaining useful life (RUL) of each device in an efficient way. The presently disclosed patent application addresses this need.

Summary

Power electronics technology plays a central role in the ongoing green transition, as it provides a means for efficient and flexible conversion and conditioning of electrical power flows between a variety of sources, loads and storage systems in power grids. Power electronic converters play an indispensable role as interfacing devices in a wide variety of transport and energy applications including smart grids, (renewable energy converters, motor load drives, high-voltage dc transmission systems, conditioning devices), aerospace, railway, electric and hybrid car drives, and consumer electronics. In this context, increasing reliance on electronic devices in such applications raises great concerns for equipment to be available when needed with a minimum risk of failure in service.

According to comprehensive industrial surveys, manufacturers of power electronic converters consider power devices (where IGBTs and MOSFETs are the most represented) as the most fragile components in power converters. An important cause for end-of-life type of failures in electronic devices is linked with cracks formed between the different conductive and insulating surfaces in the packaging structure of the semiconductor chip. These cracks are the result of accumulated fatigue of the materials, due to repeated stress and strain forces caused by differences in expansion and contraction coefficients of the materials when exposed to temperature variations. Two principal failures that occur due to exposure to such strains are bond-wire lift-offs and solder-layer failures.

In the case of electrochemical batteries, rather than catastrophic failure, accumulated fatigue typically causes performance degradation in the form of reduced maximum charge capacity and power exchange capabilities. These effects are due to the main degradation modes: the loss of lithium inventory, where lithium ions are consumed by parasitic reactions and are no longer available for the main chemical reactions; and the loss of active material of the negative and positive electrodes, in which parts of the electrode become progressively unavailable for the adhesion of lithium ions. The manifestation and combination of these phenomena is highly complex and leads to the aforementioned performance degradation. All of them may occur throughout the entire battery's lifetime, some of them being predominant at certain stages.

A typical way to quantify these effects is to perform accelerated lifetime testing of the electronic device in controlled lab environment and using the resulting cycling data to create empirical models that express an incremental damage of a certain device over a given set of stress cycles.

From an end-user's perspective, it is important to be able to predict the remaining useful lifetime (RUL) of an electronic device, so as to be able to replace it or to plan for the appropriate maintenance, before potentially catastrophic failure occurs, or the device loses its nominal functional capability. A standard way to do it today is to estimate and process the profile of stress variables, assuming that the mechanical stresses in the packaging structure of a given electronic device are a function of the stress variable variation. Since it is difficult to directly measure some device key stress variables (e.g. power electronic chip temperature, battery cell state of charge) they can be estimated. In the case of a power electronic device, a thermal model of the device in combination with the measurable device losses can be used. In case of a battery cell, a state of charge estimation algorithm can be used.

However, standard RUL estimation methods have several drawbacks; the first one is uncertainty of models for estimating SI (stress indicator) variables, which when paired with potential errors in voltage and current measurements lead to uncertainty in the device stress variable estimation. Moreover, long-term stress variable (SV) profiles in electronic devices operating in the field depend on many different factors, including the load variations, the ambient temperature, the device ageing, etc. To capture these variations and to count and quantify them, online rainflow counting algorithms need to be deployed. However, uncertainty and also potential noise in the estimated stress variables, as well as different implementations of rainflow counting algorithms can lead to high uncertainty in the number of counted stress variable cycles,. Moreover, to estimate the effect of all identified cycles on the overall damage (e.g. by summing up incremental damages using Miner's rule), empirical incremental device damage models need to be evaluated in operating conditions for which they have not been tested. In other words, there is a definite uncertainty of the parameters used in the incremental device damage models, which can lead to large potential errors in the RUL prediction. In fact, accounting only for uncertainty of few input parameters in the incremental device damage model (i.e. neglecting the uncertainties of other parameters, neglecting the uncertainty in estimated SIs (stress indicators) and disregarding the potential errors in the number of counted cycles), can lead to uncertainty in the lifetime prediction in a range of decades, which is an unacceptable margin of potential estimation error for most practical applications.

It can be concluded that the RUL estimation in traditional methods relies on several cascaded open loop empirical models, which contain numerous uncertain parameters and implementation steps, thereby leading to a highly uncertain RUL prediction.

The present disclosure relates to a method for estimation of remaining useful life or state of health of an electronic device, such as a battery, the method comprising the steps of:

- estimating state of charge (SoC) of the electronic device based on measured voltage, and/or current, and/or cell temperature using a machine learning state of charge estimation model;
- estimating an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, wherein the machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
- based on the accumulated damage, estimating the remaining useful life or the state of health of the electronic device.

The present disclosure further relates to, according to a further embodiment, a method for estimation of remaining useful life of an electronic device, such as a power semiconductor switch, the method comprising the steps of:

- estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model;
- calculating an output of a second model, the output being a temperature, such as a switch junction temperature or a solder temperature or a bonding temperature, using the second model and the estimated power loss;
- estimating an accumulated damage in the component based on the output of the second model and based on a third machine learning incremental damage model, wherein the third machine learning incremental damage model is trained with laboratory data and real-life

data from the electronic device itself and/or from similar electronic devices;

- based on the accumulated damage, estimating the remaining useful life of the electronic device.

In one embodiment of the present disclosure, the accumulated damage is predicted using a trained incremental damage model and expected mission profile. RUL (remaining useful lifetime) can thus be found, for a particular mission profile, by using the incremental damage model to predict the time required to reach the maximum allowable accumulated damage

The presently disclosed method finds relevant applications in electrical drives for fans, pumps and compressors, inverters for wind and photovoltaic plants, electrical vehicle and railway traction drives, electrical vehicle chargers and stationary and mobile batteries, and the term electronic devices is intended to be interpreted broadly, including for example power semiconductor switches, batteries or capacitors.

In a first embodiment, the presently disclosed method is used for electronic devices, such as power converters or power semiconductor switches, and targets the use of a temperature, such as a switch junction temperature or solder temperature or bond temperature as a stress variable whose cycles are used to calculate the incremental damage.

In a further embodiment, the presently disclosed method is used for electronic devices, such as battery cells, and targets the use of a cell state of charge, current and temperature as stress variables whose cycles are used to calculate the incremental damage.

The presently disclosed method may be used in several other applications in electronics and mechanics, whenever a key stress variable is identified whose historical variations are causing an incremental damage to the system.

Batteries are widely used for powering different types of systems, for example in the automotive sector, and are also suffering from reliability and degradation problems. Estimating the Remaining Useful Lifetime of a battery is very important for predictive maintenance and for avoiding malfunctioning or catastrophic end of life. An important variable that may be used for estimation of the remaining useful lifetime of a battery is, in one embodiment of the present disclosure, its state of charge, and cycles of the state of charge variable may be used for determining an incremental damage, used for estimation of the remaining useful life.

For instance, capacitors are also widely used for powering different types of systems. An important variable that can be used for estimation of the remaining useful time of life of a capacitor, or a device using a capacitor, is, in a further embodiment of the present disclosure, the capacitor's voltage, and cycles of this voltage may be used for determining an incremental damage, used for estimation of the remaining useful life.

Moreover, estimation of RUL for mechanical systems, such as motors, turbines or pumps, may be based on the use of other stress variables, like vibration or bending, whose historical cycles, in another embodiment of the presently disclosed method, may be used for determining an incremental damage, used for estimation of the remaining useful life.

One embodiment of the present disclosure provides much higher certainty in the RUL estimation result due to the fact that the first model (the loss model, used in case of power electronic devices) may be an accurate machine learning model, the second model, that computes an output relevant stress variable such as temperature, or state of charge, may be an accurate machine learning model, and the third machine learning incremental damage model provides a very accurate estimation of the accumulated damage, because the third machine learning incremental damage is trained on both laboratory data and data taken incrementally from the device itself and/or from other similar devices.

In one embodiment of the present disclosure, the first loss model and/or the second model may be empirical models if the available training data is insufficient, and therefore the RUL estimation may be hybrid, that is, based on both empirical and machine learning models.

According to one embodiment of the presently disclosed method for estimation of remaining useful life of an electronic device, RUL is estimated by use of a first power loss model, a second model capable of computing a stress variable, a rain-flow counting algorithm and a third incremental damage model which computes the accumulated damage, based on which, applying for example Miner's rule, RUL is computed.

One embodiment of the presently disclosed method overcomes critical deficiencies of traditional RUL prediction methods by replacing the empirical models in the RUL estimation chain by more accurate machine learning models.

In one embodiment of the presently disclosed application, the third model establishes an incremental electronic device damage model sustained during a given load cycle and the third model is trained by simultaneously embedding the controlled cycling lab data examples and the field data obtained from the long-term operation of the electronic device in the training process, in such a way that the machine learning based incremental damage model trained by such a process becomes "grounded" by the long-term field data, and in such a way to obtain very low uncertainty as compared to traditional methods, because the third model is trained to adhere to the reality by use of field data in the training, and not only usually limited and highly repetitive laboratory cycling data.

Typically, lifetime models obtained solely from limited laboratory cycling data analysis are usually not representative of real operation, and can make lifetime consumption predictions that are up to a few orders of magnitude away from the real device degradation. The method disclosed in this patent application may achieve uncertainty a few orders of magnitude lower than that of traditional methods since it is able to infer useful information directly from the field data.

The present disclosure further relates to a computing device comprising a processing unit configured to perform the method specified in the present disclosure.

The present disclosure further relates to a computer program having instructions which, when executed by a computing device or computing system, cause the computing device or computing system to carry out the method disclosed in the present disclosure.

The present disclosure further relates to a system comprising:

- a local processing unit, such as an edge processor; wherein the local processing unit is configured to estimate state of charge of an electronic device, such as a battery, based on measured voltage and/or current, and/or measured cell temperature and a machine learning state of charge estimation model; and wherein the local processing unit is configured to estimate an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, and wherein the local processing unit is configured to estimate the remaining useful life of the electronic device based on the accumulated damage; and
- an external computing device, wherein the external computing device is configured to train the machine learning incremental damage model, by calculating its parameters such as weights and biases, and wherein the machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device or from similar electronic devices.

The present disclosure further relates to a system comprising:

- a local processing unit, such as an edge processor; wherein the local processing unit is configured to estimate power loss of a component of an electronic device based on measured voltage and/or current, and/or switching frequency and a first loss model, and calculate an output of a second model, such as a temperature, a switch junction temperature or a solder temperature or a bonding temperature, in the component using the second model; and wherein the local processing unit is configured to estimate an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, and wherein the local processing unit is configured to estimate the remaining useful life of the electronic device based on the accumulated damage; and
- an external computing device, wherein the external computing device is configured to train the third machine learning incremental damage model, by calculating its parameters such as weights and biases, and wherein the third machine learning incremental damage model is trained

with laboratory data and real-life data from the electronic device or from similar electronic devices.

The present disclosure further relates to a method for estimation of remaining useful life of an electronic device, such as a battery or a capacitor, the method comprising the steps of:

- estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model;
- calculating an output of a second model, the output being a state of charge or a voltage, using the second model and the estimated power loss;
- estimating an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, wherein the third machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
- based on the accumulated damage, estimating the remaining useful life of the electronic device.

A person skilled in the art will recognize that the presently disclosed method for estimation of remaining useful life of an electronic device may be performed using any embodiment of the presently disclosed system.

The present disclosure further relates to a method for estimation of remaining useful life or state of health of an electronic device, such as a battery, the method comprising the steps of:

- estimating state of charge (SoC) of the electronic device based on measured voltage, and/or current, and/or cell temperature using a machine learning state of charge estimation model;
- estimating an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, wherein the machine learning incremental damage model is trained with laboratory data and

real-life data from the electronic device itself and/or from similar electronic devices; and

- based on the accumulated damage, estimating the remaining useful life or the state of health of the electronic device.

Description of the drawings

The invention will in the following be described in greater detail with reference to the accompanying drawings. The drawings are exemplary and are intended to illustrate some of the features of the presently disclosed method and system for estimation of remaining useful life of an electronic device apparatus, and are not to be construed as limiting to the presently disclosed invention.

Fig. 1 shows a schematic view of an embodiment of the presently disclosed method for estimation of remaining useful life of an electronic device.

Fig. 2 shows a schematic view of an embodiment of an edge computer for performing the presently disclosed method for estimation of remaining useful life of an electronic device.

Fig. 3 shows an overview of the system performing the presently disclosed method.

Fig. 4 shows a schematic diagram of an embodiment of the presently disclosed method, wherein the device is a power device, such as a power converter.

Fig. 5 shows a schematic diagram of an embodiment of a collection of data for training the machine learning incremental damage model, wherein training data comprises data obtained in a laboratory and wherein the device is a power device, such as a power converter.

Fig. 6 shows a schematic diagram of an embodiment of a collection of data for training the machine learning incremental damage model, wherein the training data is collected in the field, from the device itself or similar devices, and wherein the device is a power device, such as a power converter.

Fig. 7 shows a schematic diagram of an embodiment of the presently disclosed method, wherein the device is a battery.

Fig. 8 a schematic diagram of an embodiment of a collection of data for training the machine learning incremental damage model, wherein training data comprises data obtained in a laboratory and wherein the device is a battery.

Fig. 9 shows a schematic diagram of an embodiment of a collection of data for training the machine learning incremental damage model, wherein the training data is collected in the field, from the device itself or similar devices, and wherein the device is a battery.

With reference to figures 4-9, the following symbols are used.

V_{meas}: measured voltage.
I_{meas}: measured current.
f_{sw}: switching frequency.
P_{loss}: power losses in the device.
T_j: junction temperature.
$N(\Delta T_j, \overline{T_j})$: number of stress cycles counted at each pair of junction temperature swing (ΔT_j) and mean ($\overline{T_j}$).
LC: lifetime consumption.
T_{meas}: measured cell temperature.
SoC: state-of-charge of the cell.
$N(\Delta SoC, \overline{SoC})$: number of stress cycles counted at each pair of SoC swing (ΔSoC) and mean ($\overline{SoC}$).
$\hat{C}_{max}$: estimated maximum cell capacity.
C_{nom}: nominal cell capacity either estimated at the beginning of the cell's lifetime, or given by the manufacturer.

Detailed description

The present disclosure relates to a method for estimation of remaining useful life of an electronic device, such as a power semiconductor switch, the method comprising the steps of:

- estimating power loss of an electronic device;
- calculating an output of a second model;
- estimating an accumulated damage in the component; and
- estimating the remaining useful life of the electronic device.

Preferably, the step of estimating power loss of an electronic device is based on measured voltage, and/or current, and/or switching frequency using a first loss model. In the step of calculating an output of a second model, the output may be a stress variable, or a temperature, such as a switch junction temperature or a solder temperature or a bonding temperature, or state of charge, or voltage or any other lifetime relevant variable in the device. The step of estimating the current state of health of a battery cell is based on measured voltage, and/or current, and/or temperature.

The step of calculating an output of a second model preferably uses the second model and the estimated power loss or state of health or state of charge. In the step of estimating an accumulated damage in the device, the accumulated damage may be based on the output of the second model and a third machine learning incremental damage model, wherein the third machine learning incremental damage model has been trained combining laboratory data and real life and/or field operation data from the electronic device itself and/or from similar electronic devices. The step of estimating the remaining useful life of the electronic device is preferably based on the accumulated damage.

Fig. 1 shows a schematic view of an embodiment of the presently disclosed method the method (100) comprising the steps of: (101) estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model or estimating the state of health of the battery cell based on measured voltage, current and / or temperature of the cell; (102) calculating an output, such as a temperature, or state of charge or another stress variable in the device using a second model; (103) Rain-flow counting of the output of the second model; (104) estimating an accumulated damage in the component based on an output of the second model and based on a third machine learning incremental damage model; (105) based on the accumulated damage and anticipated future mission profile, estimating the remaining useful life of the electronic device.

The electronic device may be a power converter, a power semiconductor switch, a battery or a capacitor.

In one embodiment of the present disclosure, the first model, second model and third model are configured to be operated independently such that it may be possible to use a first machine learning model or a first empirical model, and a second machine learning model or a second empirical model. In one embodiment of the present disclosure, the first, second and third model are independent from each other, in such a way that if the first model is based on machine learning or is empirical, the second and/or the third model are not affected in their operation. Likewise, if the second model is based on machine learning or is empirical, the first and/or the third model are not affected in their operation.
This means that the first model may be a machine learning model or an empirical model, and the second model may be a machine learning model or an empirical model, and in the presently disclosed method it is possible to change the first and/or the second model from machine learning models to empirical models, if the data-set for the offline training of the first and/or the second model is insufficient.

In one embodiment of the present disclosure, the remaining useful life is computed based on a cumulative damage, wherein a rain-flow counting of the historical output of the second model, such as a temperature or state of charge data provides a load collective that is evaluated against the third machine learning incremental damage model using a mathematical method, such as Miner’s rule.

In a further embodiment, the third model may output the instantaneous increases in consumed lifetime ΔLC, or incremental damage, Miner's rule may be simply used to linearly sum up these contributions to obtain LC where LC is the accumulated lifetime consumption, or cumulative damage, and RUL may be estimated as the rated lifetime of the device times (1 - LC) or by obtaining the time for which LC will reach its maximum allowable value given an expected mission profile.

In a further embodiment, the first model, the second model, a rain-flow counter and the third model may be cascaded, such as cascaded in a given cardinal order.

Fig. 2 shows a schematic view of an embodiment of an computing device (208) for performing the presently disclosed method for estimation of remaining useful life of an electronic device wherein the first model (203), the second model (204), the rainflow counting (205), the third model (206), and Miner's rule (207) are performed in cascade to estimate the RUL of an electronic device (201), wherein the sensor data that are input to the first model are shown in (202).

Fig. 3 shows an overview of the system performing the presently disclosed method.

First Model

In one embodiment, relevant for the power electronic device, the first model, when executed, may be configured to estimate, in substantially real-time, the power loss of each electronic device, such as a semiconductor switch, based on measured voltage and current and the first model may be a static machine learning model. Measured voltage and/or current and/or switching frequency of the electronic device may be inputs to the first model, and the power loss may be output of this first model.

In another embodiment, relevant for the battery cell, the machine learning incremental damage model, when executed, may be configured to estimate, in substantially real-time, the state of health of battery cell, based on measured voltage and current and the first model may be a static machine learning model. Measured voltage and/or current and/or temperature of the battery cell may be inputs to the first model, and the current state of health of the battery cell may be output of this first model.

In one embodiment, especially for a power device, the first model may be a neural network, such as a single layer artificial neural network, and may be trained by many input and output measurements of power losses as a function of input variables, such as voltage and/or current and/or switching frequency, within the electronic device, used as training examples for supervised learning.

For batteries, the state of charge model may be a neural network, such as a single layer artificial neural network, and may be trained by many input and output measurements of state of charge as a function of input variables, such as measured voltage and/or measured current and/or measured cell temperature.

The first model may be configured to model the non-linear relationship between the power loss or other output variable and the input variables of the electronic device accurately, due to the universal approximation capabilities of neural networks.
In one embodiment, for power devices, the first model may be a machine learning loss model, which models a nonlinear relationship between the power loss and the input variables of the electronic device.

In one embodiment, the first loss model may be an artificial neural network.

In a further embodiment of the present disclosure, the first loss model is trained offline based on sensor data input, wherein the sensor data input is obtained from voltmeters and/or amperometers and/or thermometers and/or other types of sensors.

In a further embodiment, the first model may have obtained information about the switching frequency of the device.

Second Model

The power loss or state of health of an electronic device and/or the ambient temperature may be input to the second model, and the output of the second model may be a relevant stress variable of the electronic device, such as a switch junction temperature, or solder temperature or bonding temperature, or voltage.

In one embodiment of the present disclosure, the second model may be a Cauer or Foster network.

In a further embodiment, the output of the second model may be a switch junction temperature, or solder temperature, or bonding temperature.

In one embodiment, the second model, when executed, may calculate, in substantially real-time, the switch junction temperature for a bonding wire in each switch, based on the estimated loss of the switch.

In a further embodiment, the second model may calculate, in substantially real-time, a case temperature for a solder layer based on the power loss of the switch and a power loss of the corresponding diode.

In a further embodiment, the machine learning state of charge estimation model may calculate, in substantially real-time, a state of charge based on the measured voltage and/or current and/or temperature.

In a further embodiment of the present disclosure, the second model may be a neural network, such as a recurrent neural network, or a feed-forward neural network, and may be trained by many sequences of pairs of estimated power losses and measured chip / solder layer temperatures, used as training examples for supervised learning and wherein the second model may accurately model the nonlinear dynamic relationship between the power losses and temperatures, due to the universal approximation capability of neural networks.

In a further embodiment, if measurements for training are not available in the training process, then the Cauer or Foster thermal models may be used for the second model.

In an further embodiment, the second model may be an artificial neural network trained on pairs of estimated power losses, measured ambient temperature and measured chip / solder layer / bonding temperatures, or the second model may be an empirical model if the training data-set is insufficient.

In a further embodiment, the second model may also be using the ambient temperature as an input and the second model output may be a switch junction temperature, or a solder temperature or a bonding temperature

In another embodiment, the second model may be an artificial neural network trained on pairs of estimated power losses and another lifetime relevant variable, or the second model may be an empirical model if the training data-set is insufficient.

Third Model

The third machine learning model may generate, in substantially real-time, an incremental damage and/or an accumulated damage based on the count of a value of a relevant lifetime variable of a component of the electronic device, such as an output of the second model.

The accumulated damage may be the sum of incremental damages.

The historical value of a relevant lifetime variable of a component of the electronic device, such as an output of the second model may be counted with a cycle counter, such as a rain-flow counter, in such a way that the output of the cycle counter is used as an input to the third machine learning model.

The historical value of a relevant lifetime variable of a component of the electronic device, such as switch junction temperature, may be counted with a cycle counter, such as a rain-flow counter, in such a way that the output of the cycle counter is used as input to the third machine learning model.

In one embodiment of the present disclosure, the third machine learning model may generate, in substantially real-time, an incremental damage and/or an accumulated damage of the bonding wires in each switch of a given electronic device based on the switch junction temperature.

In a further embodiment of the present disclosure, the third machine learning model may generate, in substantially real-time, an incremental damage and/or an accumulated damage of the solder layer in each switch based on the case temperature.

In one embodiment, the third model may be a neural network, such as a feedforward neural network, and may be trained combining data from the controlled lab cycling tests and from the field failure data of power electronic systems in the supervised training process of the feedforward neural network.

In one embodiment of this disclosure, the loss function used for training of the third machine learning model has a first term and a second term and is expressed by the following equation:

$$J(\Theta) = \frac{1}{m}\sum_{i=1}^{m}\left(\mathrm{net}\left(\Delta T_{j,i}, t_{on,i}, T_{j,mean,i}, \dots\right) - \frac{1}{\Delta LC, i}\right)^2 + \lambda\,\frac{1}{n}\sum_{k=1}^{n}\left(\sum_{f=1}^{g}\left(n_{f,k}\cdot \mathrm{net}\left(\Delta T_{j,f,k}, t_{on,f,k}, T_{j,mean,f,k}, \dots\right)\right) - 1\right)^2$$

where the first term is $\frac{1}{m}\sum_{i=1}^{m}\left(\mathrm{net}\left(\Delta T_{j,i}, t_{on,i}, T_{j,mean,i}, \dots\right) - \frac{1}{\Delta LC,i}\right)^2$ and the second term is $\lambda\,\frac{1}{n}\sum_{k=1}^{n}\left(\sum_{f=1}^{g}\left(n_{f,k}\cdot \mathrm{net}\left(\Delta T_{j,f,k}, t_{on,f,k}, T_{j,mean,f,k}, \dots\right)\right) - 1\right)^2$.

In the loss function used to train the third model, the following symbols may be defined as follows:

J: Loss function for neural network training;

Θ: Parameters of the neural network (implicit in the “net” function);

$i = 1 \dots m$: Index of data sample each sample used for training;

net: Neural network function;

$\Delta T_{j,i}$: Junction temperature swing of sample i;

$t_{on,i}$: Cycle duration of sample i;

$T_{j,mean,i}$: Mean junction temperature of sample i;

$\Delta LC, i$: Lifetime consumption of sample i;

λ: Weighting factor to determine the balance between the first and second terms;

$k = 1 \dots n$: Index of each field data sample used for training;

$f = 1 \dots g$: Index of each stress level of the field data samples; and

$n_{f,k}$: Number of stress cycles at level f for sample k.

In the loss function used to train the third model, the first term may be a conventional mean squared error term present in every supervised training example, expressing that incremental damage model prediction of the neural network for a given cycle should resemble the corresponding incremental damage sustained during the same cycle during controlled laboratory tests (expressed as ΔLC).

In the loss function used to train the third model, the second term may be balanced with the first term by a weighting factor λ and it may embed historical cycling data from the field, wherein the second term states that the linear sum of all the incremental damages during the field operation of a device at the time of failure may be approximately equal to 1, and wherein the incremental damages in the second term may be estimated by the same neural network model as in the first term, but the inputs to this model may be temperature or stress variable cycles identified during the field operation, and wherein, this second term ensures that the model does not overfit only to incomplete lab data, and in this way prevents large potential errors from cumulative summation of individual incremental damages.

In a further embodiment of this disclosure, the second term of the loss function of the third model also correctly captures the influence of a specific rainflow algorithm implementation on the incremental damage model, provided that the algorithm is able to identify all key features that impact the degradation, such as junction temperature or stress variable swings and/or mean junction temperature or stress variable of each stress cycle, and/or duration of each stress cycle and/or device current and voltage, and/or "mechanical" parameters such as bond wire diameter and/or other external conditions such as ambient humidity.

It is important to highlight that standard methods use similar expression to fit the lab data with empirical models. The difference is in the way how parameters are fitted, i.e. standard models have predetermined format and fit the parameters to that model, while neural networks are a type of model that can fit any data with arbitrary precision. Therefore, standard empirical models have limited flexibility compared to neural networks to accurately fit the training data.

In another embodiment of this disclosure, the data from the field used in the second term of the loss function may be collected from a device that has failed in the field, or from a device that has not yet failed in the field and is subsequently cycled in the lab until failure.

In case of electronic devices being batteries, the inventors have realized that the use of the following loss function, for training the model, may be advantageous:

$$J(\Theta) = \frac{1}{m}\sum_{i=1}^{m}\left(\mathrm{net}(N_i(\Delta SoC, \overline{SoC}, \dots)) - \frac{1}{LC_i}\right)^2 + \lambda\,\frac{1}{n}\sum_{k=1}^{n}\left(\mathrm{net}(N_k(\Delta SoC, \overline{SoC}, \dots)) - \frac{1}{LC_k}\right)^2$$

In the loss function used to train the third model, the following symbols may be defined as follows:

J: Loss function for neural network training;

Θ: Parameters of the neural network (implicit in the “net” function);

$i = 1 \dots m$: Index of each empirical model data sample used for training;

net: Neural network function;

ΔSoC: State of charge swing of sample i;

$\overline{SoC}$: Mean state of charge of sample i;

LC_i: Lifetime consumption of sample i;

λ: Weighting factor to determine the balance between the first and second terms;

$k = 1 \dots n$: Index of each field data sample used for training; and

N_i: Number of stress cycles corresponding to sample i.

Also in the loss function used for batteries the second term may be balanced with the first term by a weighting factor λ and it may embed historical cycling data from the field. Therefore, for training, both data from the field and from laboratory is used, yielding very good results in terms of accuracy and/or consistency and/or robustness.

In one embodiment, for power electronic device, once the device is failed, the incremental damage model may be updated/retained.

In another embodiment, for battery cell: current state of health may be estimated and may be used to train the incremental damage model periodically during the entire lifetime of the cell. Reliable state of health estimations may be obtained through Coulomb counting over large charge/discharge cycles.

In a further embodiment, the third model may be updated progressively as more data from failed or degraded field devices is collected.

In one embodiment of the present disclosure, the incremental damage is computed by the third model based on a historical switch junction temperature or stress variable profile, or solder temperature profile, or bonding temperature profile, or based on a historical profile of a state of charge or voltage or another lifetime relevant variable, such as a stress variable, or an output of the second model.

In one embodiment, the historical temperature profile of a switch junction, or a solder or a bonding, such as a bonding wire or bonding connection, may be used by the third model to generate a load collective used for the computation of the incremental damage.

In a further embodiment, the historical variations of the historical profile of a state of charge of a battery may be used by the third model to generate a load collective used for the computation of the incremental damage.

In a further embodiment, the historical variations of the voltage of a capacitor may be used by the third model to generate a load collective used for the computation of the incremental damage.

In a further embodiment, the historical variations of a stress variable of a system may be used by the third model to generate a load collective used for the computation of the incremental damage.

In a further embodiment, the third model comprises a loss function with a term based on laboratory data generated from stress test or other test, and a term based on historical cycling data from the field, and wherein the loss function is used for supervised offline training of the model, and wherein the data from the field, or historical cycling data, is collected at failure of some electronic devices similar to the electronic device.

In a further embodiment, the third model is trained using a loss function wherein the term based on historical cycling data is balanced with the term based on laboratory data with a weighing factor.

Rainflow counting

In one embodiment, a rain-flow counting, or cycle counting, of the output of the second machine learning model may be computed as an input to the third machine learning model.

In a further embodiment, a modified rain-flow counting method may be implemented, in which the intervals used for assigning a cycle to a histogram bin are replaced by a fuzzy-logic-based system with diverse membership functions.

Systems

In one embodiment of the present disclosure, the first model and the second model and the calculations using the first model and the second model are performed on a local device, such as a microcontroller.

All calculations of the presently disclosed method may be performed in substantially real-time. ‘Substantially real-time’ in the context of the present disclosure has the broad meaning that the calculations can be carried out in a way that a user can obtain information about the remaining useful life of an electronic device without substantial delay i.e. there is no need for e.g. complex simulations on servers or sending large amounts of data. In one embodiment of the present disclosure, all the models may be trained offline. In a further embodiment of the present application, all the calculations based on all the models are computed on an edge computer, such as a microcontroller, that is located locally in, or in connection to the electronic device. An edge computer may be configured to compute all needed calculations within a predefined limit, such as within a millisecond, or within one micro-second.

The present disclosure further relates to a computing device comprising a processing unit configured to perform the method according to any one of the preceding claims.

The present disclosure further relates to a computer program having instructions which, when executed by a computing device or computing system, cause the computing device or computing system to carry out the method according to the present disclosure.

The present disclosure further relates to a system comprising:

- a local processing unit, such as an edge processor; wherein the local processing unit is configured to estimate power loss of a component of an electronic device based on measured voltage and/or current, and/or switching frequency and a first loss model, and calculate an output of a second model, such as a temperature, a switch junction temperature or a solder temperature or a bonding temperature, in the component using the second model; and wherein the local processing unit is configured to estimate an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, and wherein the local processing unit is configured to estimate the remaining useful life of the electronic device based on the accumulated damage; and
- an external computing device, wherein the external computing device is configured to train the third machine learning incremental damage model, by calculating its parameters such as weights and biases, and wherein the third machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device or from similar electronic devices.

In one embodiment, the presently disclosed system may be such that the local processing unit and the external computing device are connected to each other by a wireless connection.

In a further embodiment of the presently disclosed system, the local processing unit is part of a power converter hardware unit.

Fig. 4 shows a schematic diagram of an embodiment of the presently disclosed method, wherein the device is a power device (401), such as a power converter. A first loss model (203) is used to calculate output power loss (403) from input measured voltage and/or input measured current and/or input measured switching frequency (402). A second model (204) is used to calculate a junction temperature (404) based on input power loss (403). A third machine learning model (206) is used to calculate lifetime consumption or accumulated damage (406) based on junction temperature (404) or based on output of rainflow counter (205), wherein input of the rainflow counter is the junction temperature and output of the rainflow counter is a number of stress cycles counted at each pair of junction temperature swing.

In one embodiment of the present disclosure the machine learning incremental damage model is trained based on a combination of data collected in a laboratory and data collected in the field.

Fig. 5 shows how a training data set for the machine learning incremental damage model is collected in the laboratory, in one embodiment of the present application, for a power device. In the laboratory the machine learning incremental damage model is substituted with an empirical damage model (504) which calculates the accumulated damage or lifetime consumption (505). The data so obtained is used, in combination with data retrieved in the field, to train the machine learning incremental damage model.

Fig. 6 shows how a training data set for the machine learning incremental damage model is collected in the field. Junction temperature (503) is collected during normal operation until end of life or failure, that is, when lifetime consumption is known to have reached end of life. The collected data from the field is then used, in combination with data from laboratory, to train the machine learning incremental damage model.
Using a combination of training data from the laboratory and the field increases the accuracy of the prediction of the accumulated damage as compared to methods that only rely on laboratory data. This is because laboratory data are typically comprising stress cycles that are different from the stress cycles the device undergoes in real applications in the field. In addition, in this way, the machine learning incremental damage model may be trained in the cloud, or remotely, with data collected on the device by an edge processor.

In one embodiment, the machine learning incremental damage model may therefore run on the edge processor in the device but may be trained remotely. Updated model after training may then be sent to the edge processor in the device for damage prediction. This has the advantage to unload the edge processor from the burden of training the machine learning incremental damage model but the machine learning incremental damage model may be adaptively trained remotely by a computer with, for example, more resources.

In one embodiment of the present disclosure, for power converters, new training samples (pairs of stress cycles-accumulated damage) occur only at failure of the edge devices, since accurate assessments of the health of power devices are costly and often require their disassembly. Therefore, the damage model runs on the edge processor in the device and, at failure, the new sample is sent to the cloud, where the incremental damage model is updated. The updated model would then be periodically communicated back to the edge processor in the devices.

Batteries and Capacitors

The present disclosure relates to a method for estimation of remaining useful life or state of health of an electronic device, such as a battery, the method comprising the steps of:

- estimating state of charge (SoC) of the electronic device based on measured voltage, and/or current, and/or cell temperature using a machine learning state of charge estimation model;
- estimating an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, wherein the machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
- based on the accumulated damage, estimating the remaining useful life or the state of health of the electronic device.

In one embodiment of the presently disclosed method, the electronic device may be a battery.

The inventors have realized that, for accurate calculation of state of charge of a battery, it is advantageous to account also for a cell temperature as methods based on fixed-temperature discharge event and extrapolation of the temperatures are less accurate.

The inventors have further realized that using machine learning techniques for the estimation of the state of charge is more accurate than using Coulomb counting.

The inventors have further realized that using the state of charge, or a rainflow counted state of charge, as input to the machine learning incremental damage model is advantageous as compared to using directly the inputs of the machine learning state of charge estimation model as inputs to the machine learning incremental damage model as that reduces the complexity of the machine learning incremental damage model and makes it possible to run on an edge processor at the device, that is a processor located close to the device. Using the cycles from the rainflow algorithms allows for a representation of the stress variable more suited to be processed by the machine learning algorithms. The information contained in the original time series can be condensed into a set of features of interest (e.g., range, mean) without significant loss of information. One of the most relevant advantages is the reduction of memory requirements for the edge processor.

The present disclosure further relates to a method for estimation of remaining useful life of an electronic device, such as a battery or a capacitor, the method comprising the steps of:

- estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model;
- calculating an output of a second model, the output being a state of charge or a voltage, using the second model and the estimated power loss;
- estimating an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, wherein the third machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
- based on the accumulated damage, estimating the remaining useful life of the electronic device.

In one embodiment of the present disclosure the electronic device may comprise a battery and the state of charge of the battery may be a stress variable as an output of the second model. The historical profile of the state of charge may be used by the third model to compute incremental damage, and finally estimate remaining useful life of the device.

In a further embodiment of the present disclosure the electronic device may comprise a capacitor and the voltage of the capacitor may be a stress variable calculated as an output of the second model. The historical profile of the voltage may be used by the third model to compute incremental damage, and finally estimate remaining useful life of the device.

Fig. 7 shows a schematic diagram of an embodiment of the presently disclosed method, wherein the device is a battery (703). According to one embodiment of the presently disclosed method, a machine learning state of charge estimation model (701) is used to estimate the output state of charge from input measured voltage and/or input measured current and/or input cell temperature. According to one embodiment, the machine learning incremental damage model (702) is used to estimate accumulated damage of lifetime consumption or state of health of the electronic device. Between the output of the machine learning state of charge estimation model and the input of the machine learning incremental damage model there may be a rainflow counter, which has the state of charge as input and, as output, the number of stress cycles counted at each pair of SoC swing (ΔSoC) and mean ($\overline{SoC}$).

In one embodiment of the present disclosure, the machine learning incremental damage model may be trained by a combination of training data from the laboratory and training data from the field. Using a combination of training data from the laboratory and the field increases the accuracy of the prediction of the accumulated damage as compared to methods that only rely on laboratory data. This is because laboratory data are typically comprising stress cycles that are different from the stress cycles the device undergoes in real applications in the field.

In one embodiment, the machine learning incremental damage model may therefore run on the edge processor in the device but may be trained remotely. The updated model after retraining may then be sent to the edge processor at the device for damage prediction. This has the advantage to unload the edge processor from the burden of training the machine learning incremental damage model but the machine learning incremental damage model may be adaptively and remotely trained by a computer with, for example, more resources.

The machine learning incremental damage model may be trained incrementally by continuously collecting data from the field. The machine learning incremental damage model may therefore undergo an adaptive training process, influenced by training data coming from the field, by the same device or similar device, and therefore the damage predicted by the machine learning incremental damage model may be very accurate because it is tailored to the application of the device.

Fig. 8 shows, in one embodiment of the present disclosure, when the electronic device is a battery, how training data from the laboratory is collected. During the collection of such data the machine learning incremental damage model is substituted with a an empirical damage model (806) that calculates the accumulated damage (806) and the obtained data, together with the input data, forms a laboratory-based training data-set.

Fig. 9 shows, in one embodiment of the present disclosure, when the electronic device is a battery, how training data from the field is collected. In this embodiment the machine learning state of charge estimation model also outputs an estimated maximum capacity, and that is used to estimate the accumulated damage for each charge/discharge cycle. The obtained training data is used to train the machine learning incremental damage model, in combination with data taken from the laboratory.

In one embodiment of the present disclosure, for batteries, the present method does not require to wait until failure to obtain new samples, as during full (or close to full) charge and discharge cycles, the method may obtain reliable estimates of the SoH of the battery. These are then sent to the cloud to update the incremental damage model.

In the presently disclosed method, when applied to converters, reliable measurements of lifetime consumption can typically only be obtained at points of failure (at the end of the lifetime). This is because an in-depth analysis of the health status of power electronics components (such as an IGBT) is typically destructive or at least requires

their disassembly, and is therefore not commonly performed in field operations. On the other hand, the health status of batteries is typically defined in terms of remaining maximum capacity or state of health (SoH), which can be reliably estimated during operation by performing a complete charge or discharge cycle.
For the purposes of the presently disclosed method, this means that, for converters, samples from field data can only be obtained at the end of the components' lifetime, while, for batteries, they can be obtained at any point when a full cycle occurs, either during normal operation or in a forced manner.

In one embodiment of the present disclosure, the battery's state of health (SoH) may be reliably estimated by means of Coulomb counting (numerically integrating current measurements) over a full charge and/or discharge cycle. Other methods may be based on voltage and/or current and/or temperature measurements and involve machine learning algorithms (e.g. neural networks or extreme-learning machines); incremental capacity, differential voltage, or current pulses; or the aggregation of several estimations from independent models.

In the present disclosure, state of health (SoH) of a battery and the lifetime consumption LC or the accumulated damage are related to each other.

In particular, for batteries, it is common to define SoH as:

$$SoH(t) = \frac{C(t)}{C_{ref}}$$

Where $C(t)$ is the maximum battery capacity measured or estimated at time t , and C_{ref} is the reference capacity. These are typically expressed in kilowatt-hours or ampere-hours. $C(t)$ may be either measured by performing full charge/discharge cycles or estimated by, among others, partial charge curves, incremental capacity analysis or impedance measurements. The reference capacity (C_{ref}) is taken as the rated capacity given by the manufacturer, or the capacity measured in the first cycles. Maximum capacity ($C(t)$) may be either measured by performing full charge/discharge cycles or estimated by, among others, partial charge curves, incremental capacity analysis or impedance measurements.

A minimum value for SoH is typically considered to correspond to a "failure", such as 80%, 70%, 50%, etc. One can therefore relate LC to SoH as:

$$LC = \frac{1 - SoH}{1 - SoH_{min}}$$

In one embodiment of the present disclosure, inputs to the machine learning state of charge estimation model may be measured voltage of the electronic device, and/or measured current of the electronic device and/or measured cell temperature of the electronic device.

In one embodiment of the present disclosure, training data of the machine learning incremental damage model comprise laboratory data for training obtained by using an empirical damage model for the calculation of accumulated damage and/or life consumption and/or state of health.

In one embodiment of the present disclosure, input to the empirical damage model, used to collect training data, may be the same input as for the machine learning incremental damage model, said input being an estimated state of charge and/or an output of a rainflow counter of the estimated state of charge.

In one embodiment of the present disclosure, training data of the machine learning incremental damage model may comprise real-life data for training obtained by running complete charge/discharge cycles of the device or similar device. This adaptive learning of the machine learning incremental damage model, based on training data also from the field, renders the damage prediction very accurate because it is tailored to the specific application of the device.

In one embodiment of the present disclosure, the machine learning state of charge estimation model may further output an estimated state of charge and/or an estimated maximum capacity of the device.

In one embodiment of the present disclosure, training data of the machine learning incremental damage model may comprise real-life data of accumulated damage or life consumption or a state of health obtained from the estimated maximum capacity of the device.

In one embodiment of the present disclosure, inputs to the machine learning incremental damage model may be state of charge estimated by the machine learning state of charge estimation model and/or an output of a rainflow counter of the state of charge.

In one embodiment of the present disclosure, output of the rainflow counter is a number of stress cycles counted at each pair of swings of state of charge and mean state of charge and input of the rainflow counter is the state of charge of the device.

In one embodiment of the present disclosure, the machine learning state of charge estimation model may further output a voltage, such as a voltage of the device or the capacitor.

The machine learning incremental damage model does not receive, as inputs, directly measured current and/or measured voltage and/or, in the case of batteries, measured cell temperature. On the contrary, the state of charge estimation model outputs a state of charge, which is an input to the machine learning incremental damage model, either directly or via a rainflow counter. That is advantageous because it reduces the complexity of the machine learning incremental damage model which is deployed, in one embodiment of the present disclosure, typically in a local processor in the edge, close to the device, while trained remotely.

In one embodiment of the present disclosure, the state of charge may be the input to the rainflow counting algorithm, which may in turn feed into the machine learning incremental damage model. Running through rainflow counting may allow for reduced model complexity (due to a more "favourable" data representation) and it may reduce the amount of data to be stored, which is often a limiting factor in microcontroller devices.

The machine learning incremental damage model does not receive, as inputs, directly measured current and/or measured voltage and/or, in case of power converters, switching frequency. On the contrary, the machine learning incremental damage model receives as input the output of another model. That is advantageous because it reduces the complexity of the machine learning incremental damage model which is deployed, in one embodiment of the present disclosure, typically in a local processor in the edge, close to the device, while trained remotely.

The presently disclosed method, thanks to the type of training based on laboratory and field data, does not require the use of datasheet provided by the manufacturer and may be applied to the device directly.

The presently discussed method may be used during all types of operations of the device and does not require a separate machine learning incremental damage model for a “normal” operating condition and a “fast transient” operating condition. As the machine learning incremental damage model is trained on real data from the field, as well as laboratory data, a single machine learning incremental damage model, in the present disclosure, may calculate incremental damage and/or life consumption of the device in all operating conditions of the device.

Further details

1. A method for estimation of remaining useful life of an electronic device, such as a power semiconductor switch, the method comprising the steps of:
    - estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model;
    - calculating an output of a second model, the output being a temperature, such as a switch junction temperature or a solder temperature or a bonding temperature, using the second model and the estimated power loss;
    - estimating an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, wherein the third machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
    - based on the accumulated damage, estimating the remaining useful life of the electronic device.

2. The method according to item 1, wherein the electronic device is a power semiconductor switch.

3. The method according to any one of the preceding items, wherein the first model is a machine learning loss model.

4. The method according to any one of the preceding items, wherein the output of the second model is a switch junction temperature, or solder temperature, or bonding temperature.

5. The method according to any one of the preceding items, wherein an incremental damage is computed based on a historical switch junction temperature profile, or solder temperature profile, or bonding temperature profile.

6. The method according to any one of the preceding items, wherein the first loss model is an artificial neural network configured to model a nonlinear loss relationship.

7. The method according to any one of the preceding items, wherein the first loss model is trained based on sensor data input, wherein the sensor data input is obtained from voltmeters and/or amperometers and/or thermometers and/or other types of sensors.

8. The method according to item 6-7, wherein the first model has obtained information about the switching frequency of the device.

9. The method according to any one of the preceding items, wherein the second model is an artificial neural network trained on pairs of estimated power losses, measured ambient temperature and measured chip / solder layer / bonding temperatures, or the second model is an empirical model if the training data-set is insufficient.

10. The method according to item 9, wherein the second model is also using the ambient temperature as an input and wherein the second model output is a switch junction temperature, or a solder temperature or a bonding temperature.

11. The method according to any one of items 1-8, wherein the second model is an artificial neural network trained on pairs of estimated power losses and temperatures, or the second model is an empirical model if the training data-set is insufficient.

12. The method according to any one of the preceding items, wherein the third model comprises a loss function with a term based on laboratory data generated from stress test or other test, and a term based on historical cycling data from the field, and wherein the loss function is used for supervised offline training of the model, and wherein the data from the field, or historical cycling data, is collected at failure of some electronic devices similar to the electronic device.

13. The method according to any one of the preceding items, wherein the third model is trained using a loss function wherein the term based on historical cycling data is balanced with the term based on laboratory data with a weighing factor.

14. The method according to any one of the preceding items, wherein the remaining useful life is computed based on a cumulative damage, wherein a rain-flow counting of the historical output of the second model, such as a switch junction temperature or solder temperature, or bonding temperature data provides a load collective that is evaluated against the third machine learning incremental damage model using a mathematical method, such as Miner’s rule.

15. The method according to any one of the preceding items, wherein the rain-flow counting, or cycle counting, of the output of the second machine learning model is computed as an input to the third machine learning model.

16. The method according to any one of the preceding items, wherein the first model and the second model and the calculations using the first model and the second model are performed on a local device, such as a microcontroller.

17. The method according to any one of the preceding items, wherein all calculations are performed in substantially real-time.

18. The method according to any one of the preceding items, wherein the models are trained offline.

19. The method according to any one of the preceding items, wherein all the calculations based on all the models are computed on an edge computer, such as a microcontroller, that is located locally in, or in connection to the electronic device.

20. The method according to any one of the preceding items, wherein an edge computer is configured to compute all needed calculations within a predefined limit, such as within a millisecond, or within one micro-second.

21. The method according to any one of the preceding items, wherein the first model, the second model, a rain-flow counter and the third model are cascaded, such as cascaded in a given cardinal order.

22. A computing device comprising a processing unit configured to perform the method according to any one of the preceding items.

23. A computer program having instructions which, when executed by a computing device or computing system, cause the computing device or computing system to carry out the method according to any one of items 1-21.

24. A system comprising:
    - a local processing unit, such as an edge processor; wherein the local processing unit is configured to estimate power loss of a component of an electronic device based on measured voltage and/or current, and/or switching frequency and a first loss model, and calculate an output of a second model, such as a temperature, a switch junction temperature or a solder temperature or a bonding temperature, in the component using the second model; and wherein the local processing unit is configured to estimate an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, and wherein the local processing unit is configured to estimate the remaining useful life of the electronic device based on the accumulated damage; and

- an external computing device, wherein the external computing device is configured to train the third machine learning incremental damage model, by calculating its parameters such as weights and biases, and wherein the third machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device or from similar electronic devices.

25. The system according to item 24, wherein the local processing unit and the external computing device are connected to each other by a communication link, such as a wireless connection.

26. The system according to any one of items 24-25, wherein the local processing unit is part of a power converter hardware unit.

27. A method for estimation of remaining useful life of an electronic device, such as a battery or a capacitor, the method comprising the steps of:
    - estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model;
    - calculating an output of a second model, the output being a state of charge or a voltage, using the second model and the estimated power loss;
    - estimating an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, wherein the third machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
    - based on the accumulated damage, estimating the remaining useful life of the electronic device.

Claims

1. A method for estimation of remaining useful life or state of health of an electronic device, such as a battery, the method comprising the steps of:
   - estimating state of charge (SoC) of the electronic device based on measured voltage, and/or current, and/or cell temperature using a machine learning state of charge estimation model;
   - estimating an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, wherein the machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
   - based on the accumulated damage, estimating the remaining useful life or the state of health of the electronic device.

2. The method according to claim 1, wherein inputs to the machine learning state of charge estimation model are measured voltage of the electronic device, and/or measured current of the electronic device and/or measured cell temperature of the electronic device.

3. The method according to any one of the preceding claims, wherein the electronic device is a battery.

4. The method according to any one of the preceding claims, wherein training data of the machine learning incremental damage model comprise laboratory data for training obtained by using an empirical damage model for the calculation of accumulated damage and/or life consumption and/or state of health.

5. The method according to claim 4, wherein input to the empirical damage model is the same input as for the machine learning incremental damage model, said input being an estimated state of charge and/or an output of a rainflow counter of the estimated state of charge.

6. The method according to any one of the preceding claims, wherein training data of the machine learning incremental damage model comprise real life and/or

field operation data for training obtained by running complete charge/discharge cycles of the device or of a similar device.

7. The method according to any one of the preceding claims, wherein the machine learning state of charge estimation model further outputs an estimated state of charge.

8. The method according to claim 6 and 7, wherein training data of the machine learning incremental damage model comprise real life and/or field operation data of accumulated damage or life consumption or a state of health obtained from the estimated or nominal maximum capacity of the device.

9. The method according to any one of the preceding claims, wherein inputs to the machine learning incremental damage model are state of charge estimated by the machine learning state of charge estimation model and/or an output of a rainflow counter of the state of charge.

10. The method according to claim 9, wherein output of the rainflow counter is a number of stress cycles counted at each pair of swings of state of charge and mean state of charge and input of the rainflow counter is the state of charge of the device.

11. A system comprising:
    - a local processing unit, such as an edge processor; wherein the local processing unit is configured to estimate state of charge of an electronic device, such as a battery, based on measured voltage and/or current, and/or measured cell temperature and a machine learning state of charge estimation model; and wherein the local processing unit is configured to estimate an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, and wherein the local processing unit is configured to estimate the remaining useful life of the electronic device based on the accumulated damage; and
    - an external computing device, wherein the external computing device is configured to train the machine learning incremental damage model, by calculating its parameters such as weights and biases, and wherein the

machine learning incremental damage model is trained with laboratory data and real life and/or field operation data from the electronic device or from similar electronic devices.

12. A method for estimation of remaining useful life of an electronic device, such as a power semiconductor switch, the method comprising the steps of:
    - estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model;
    - calculating an output of a second model, the output being a temperature, such as a switch junction temperature or a solder temperature or a bonding temperature, using the second model and the estimated power loss;
    - estimating an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, wherein the third machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices; and
    - based on the accumulated damage, estimating the remaining useful life of the electronic device.

13. The method according to claim 12, wherein the electronic device is a power semiconductor switch.

14. The method according to any one of claims 12-13, wherein the first loss model is an artificial neural network configured to model a nonlinear loss relationship.

15. The method according to any one of claims 12-14, wherein the first loss model is trained based on sensor data input, wherein the sensor data input is obtained from voltmeters and/or amperometers and/or thermometers and/or other types of sensors.

16. The method according to claims 14-15, wherein the first model has obtained information about the switching frequency of the device.

17. The method according to any one of claims 12-16, wherein the second model is an artificial neural network trained on pairs of estimated power losses,

measured ambient temperature and measured chip / solder layer / bonding temperatures, or the second model is an empirical model if the training data-set is insufficient.

18. The method according to any one of claims 12--17, wherein the third model comprises a loss function with a term based on laboratory data generated from stress test or other test, and a term based on historical cycling data from the field, and wherein the loss function is used for supervised offline training of the model, and wherein the data from the field, or historical cycling data, is collected at failure of some electronic devices similar to the electronic device.

19. The method according to any one claims 12-18, wherein the third model is trained using a loss function wherein the term based on historical cycling data is balanced with the term based on laboratory data with a weighing factor.

20. The method according to any one of claims 13-19, wherein the remaining useful life is computed based on a cumulative damage, wherein a rain-flow counting of the historical output of the second model, such as a switch junction temperature or solder temperature, or bonding temperature data provides a load collective that is evaluated against the third machine learning incremental damage model using a mathematical method, such as Miner's rule.

21. The method according to any one of claims 12-20, wherein the first model and the second model and the calculations using the first model and the second model are performed on a local device, such as a microcontroller.

22. The method according to any one of the preceding claims, wherein all calculations are performed in substantially real-time.

23. The method according to any one of the preceding claims, wherein the machine learning incremental damage model computes accumulated damage and/or life consumption of the device in all operating conditions.

24. A computing device comprising a processing unit configured to perform the method according to any one of the preceding claims.

25. A computer program having instructions which, when executed by a computing device or computing system, cause the computing device or computing system

to carry out the method according to any one of claims 1-22 or any one of claims 12-23.

26. A system comprising:

- a local processing unit, such as an edge processor; wherein the local processing unit is configured to estimate power loss of a component of an electronic device based on measured voltage and/or current, and/or switching frequency and a first loss model, and calculate an output of a second model, such as a temperature, a switch junction temperature or a solder temperature or a bonding temperature, in the component using the second model; and wherein the local processing unit is configured to estimate an accumulated damage in the component based on the output of the second model and a third machine learning incremental damage model, and wherein the local processing unit is configured to estimate the remaining useful life of the electronic device based on the accumulated damage; and
- an external computing device, wherein the external computing device is configured to train the third machine learning incremental damage model, by calculating its parameters such as weights and biases, and wherein the third machine learning incremental damage model is trained with laboratory data and real life and/or field operation data from the electronic device or from similar electronic devices.

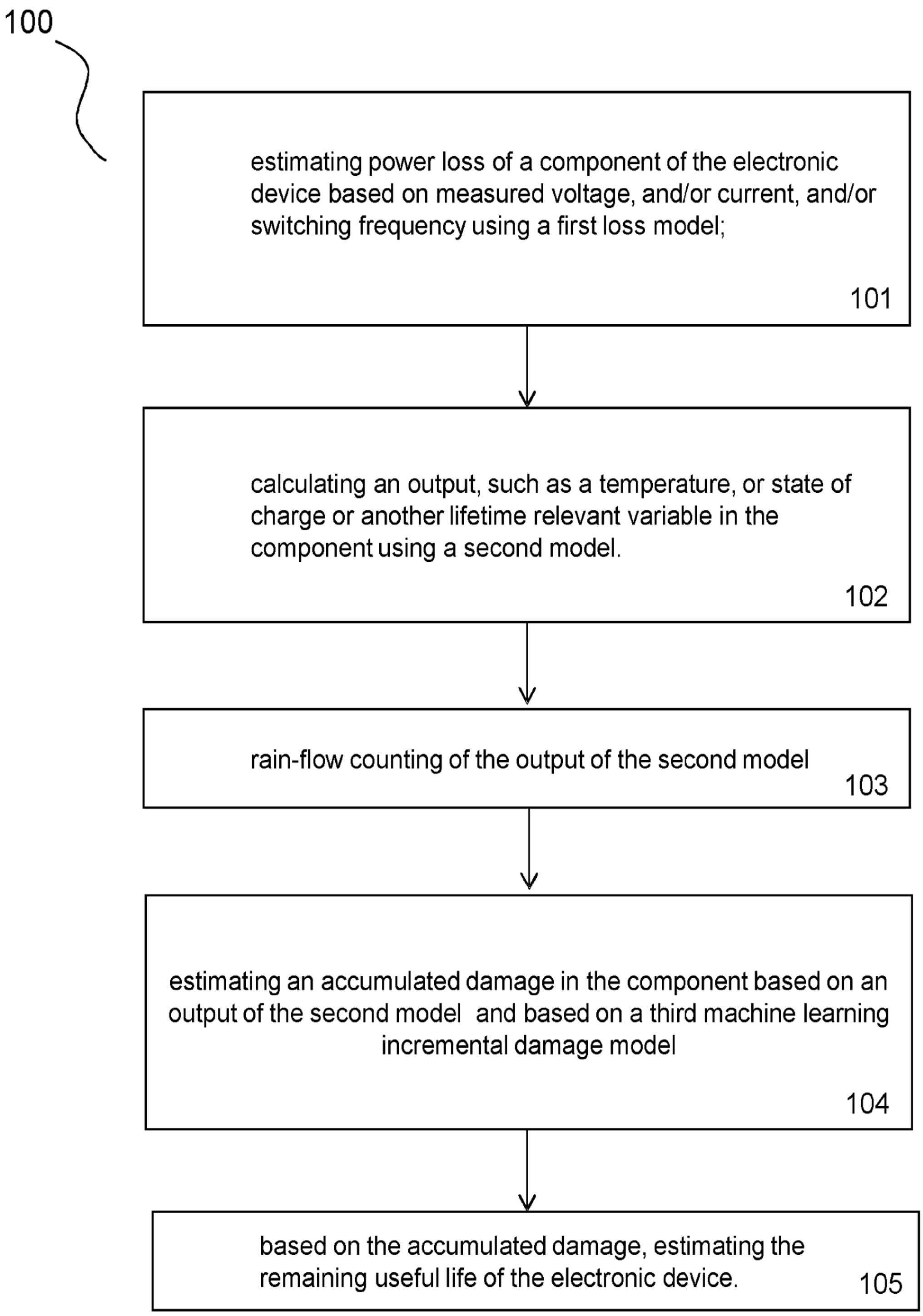
100
estimating power loss of a component of the electronic device based on measured voltage, and/or current, and/or switching frequency using a first loss model;
101
calculating an output, such as a temperature, or state of charge or another lifetime relevant variable in the component using a second model.
102
rain-flow counting of the output of the second model
103
estimating an accumulated damage in the component based on an output of the second model and based on a third machine learning incremental damage model
104
based on the accumulated damage, estimating the remaining useful life of the electronic device.
105

FIG. 1

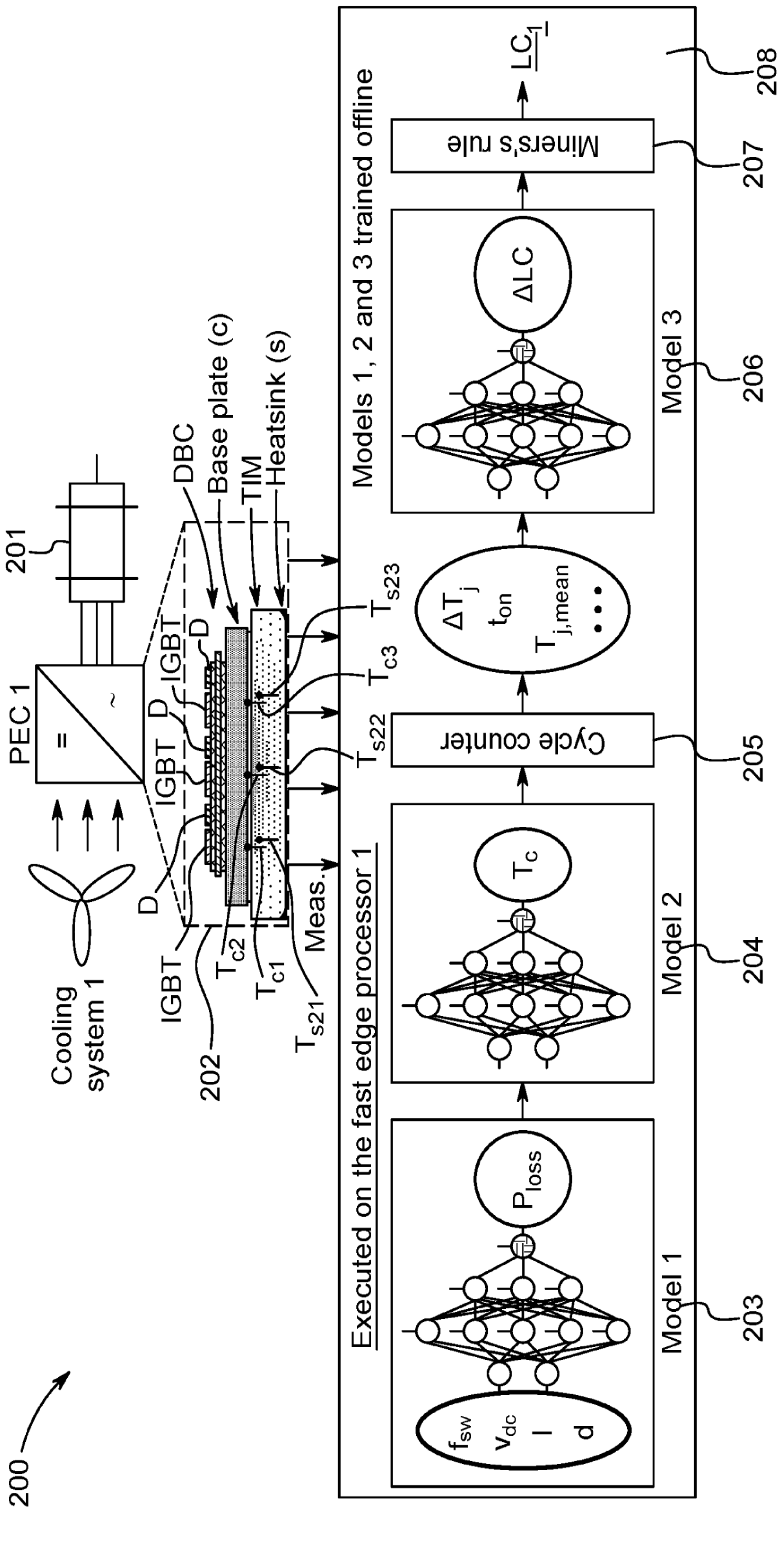
200
Cooling system 1
PEC 1
=
~
201
202
IGBT
D
DBC
Base plate (c)
TIM
Heatsink (s)
T_{c1}
T_{c2}
T_{c3}
T_{s21}
T_{s22}
T_{s23}
Meas.
Executed on the fast edge processor 1
Models 1, 2 and 3 trained offline
f_{sw}
v_{dc}
I
d
P_{loss}
Model 1
203
T_c
Model 2
204
Cycle counter
205
ΔT_j
t_{on}
$T_{j,mean}$
Model 3
206
ΔLC
Miners's rule
207
LC_1
208

FIG. 2

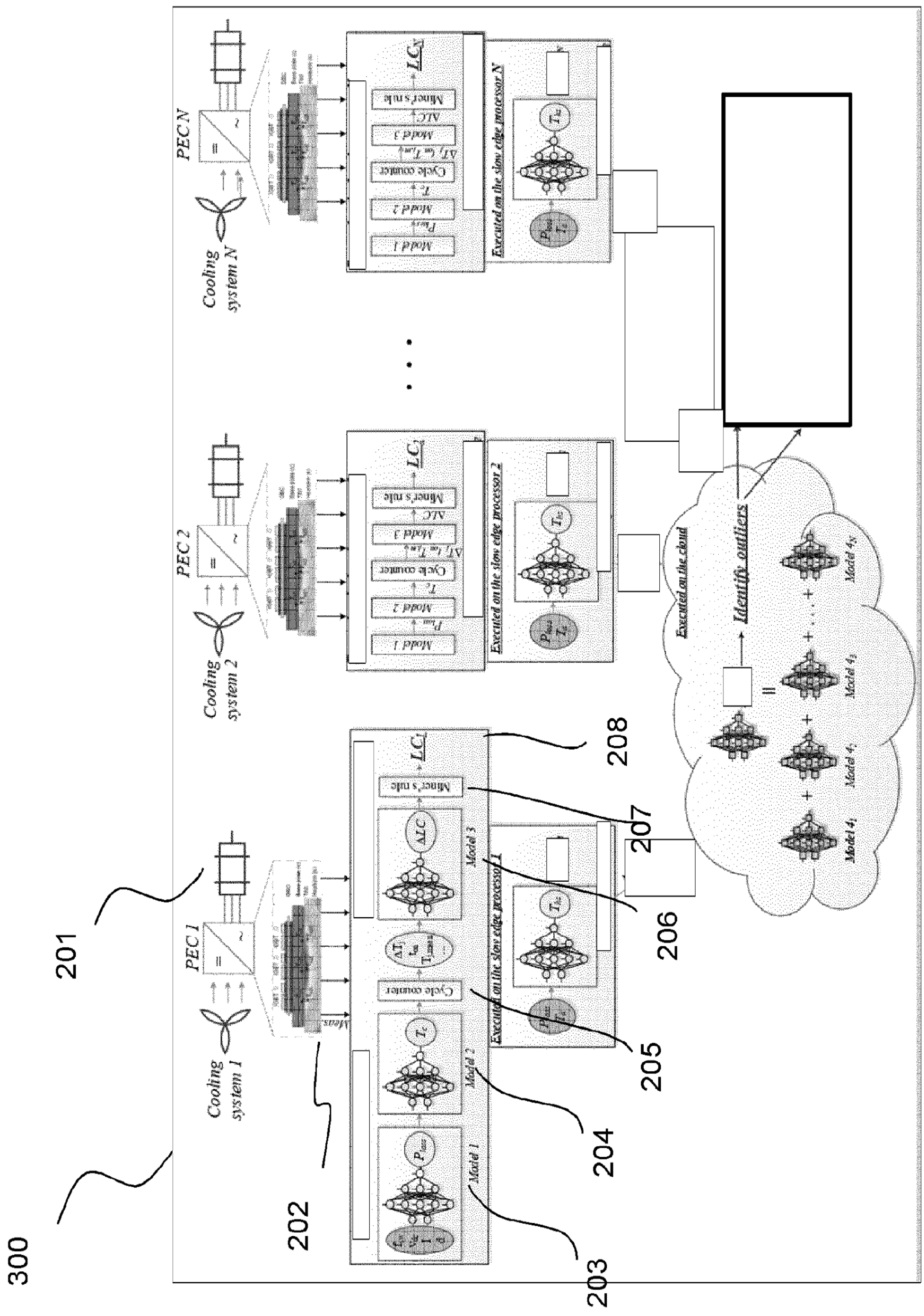
300
201
202
203
204
205
206
207
208
Cooling system 1
PEC 1
Model 1
Model 2
Model 3
Cycle counter
Miner's rule
Executed on the slow edge processor 1
Cooling system 2
PEC 2
Executed on the slow edge processor 2
Cooling system N
PEC N
Executed on the slow edge processor N
Executed on the cloud
Identify outliers

FIG. 3

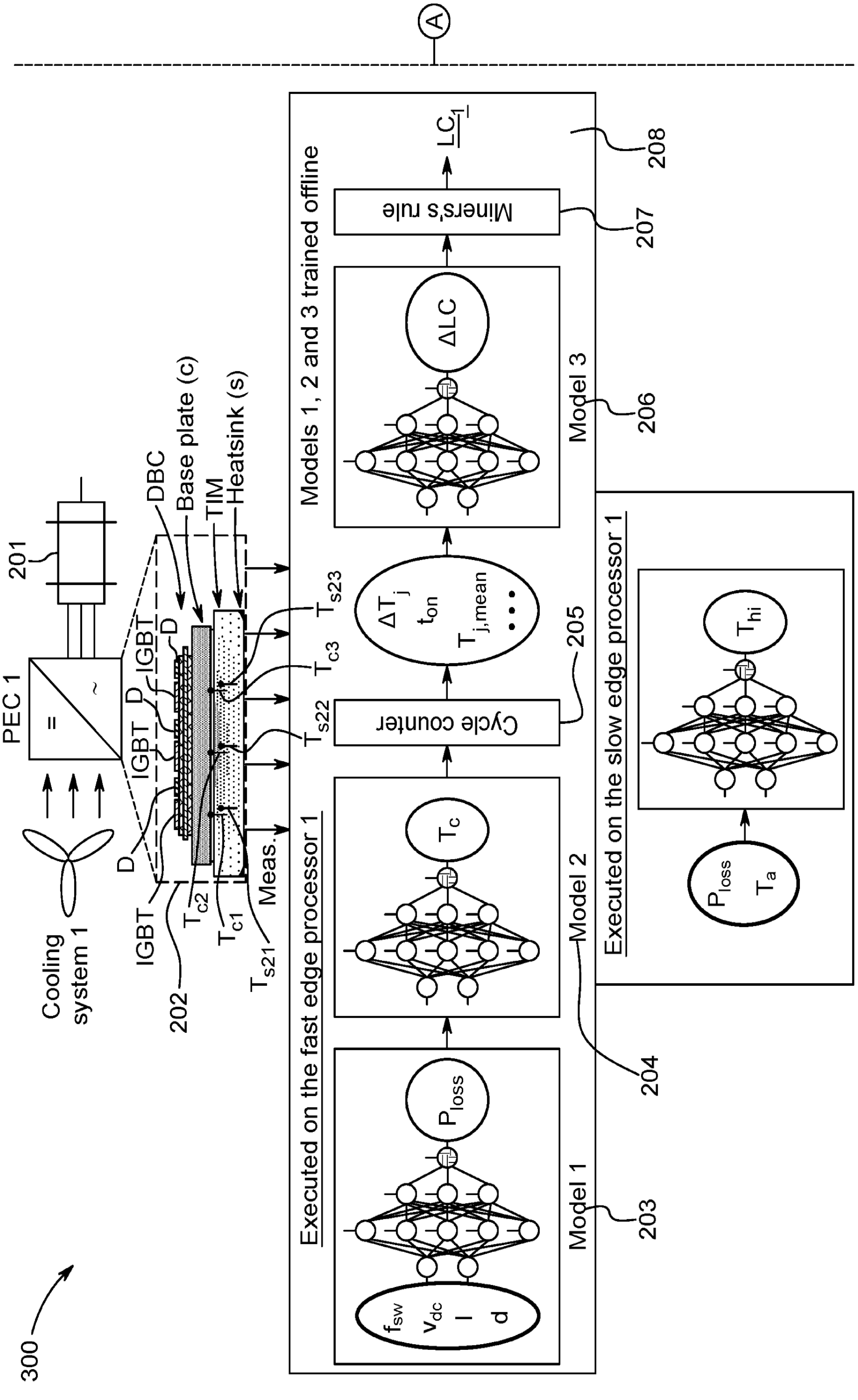
300
Cooling system 1
PEC 1
=
~
201
202
IGBT
D
DBC
Base plate (c)
TIM
Heatsink (s)
Meas.
T_{c1}
T_{c2}
T_{c3}
T_{s21}
T_{s22}
T_{s23}
A
Executed on the fast edge processor 1
Models 1, 2 and 3 trained offline
f_{sw}
v_{dc}
I
d
P_{loss}
Model 1
203
T_c
Model 2
204
Cycle counter
205
ΔT_j
t_{on}
$T_{j,mean}$
ΔLC
Model 3
206
Miners's rule
207
LC_1
208
Executed on the slow edge processor 1
P_{loss}
T_a
T_{hi}

FIG. 3A

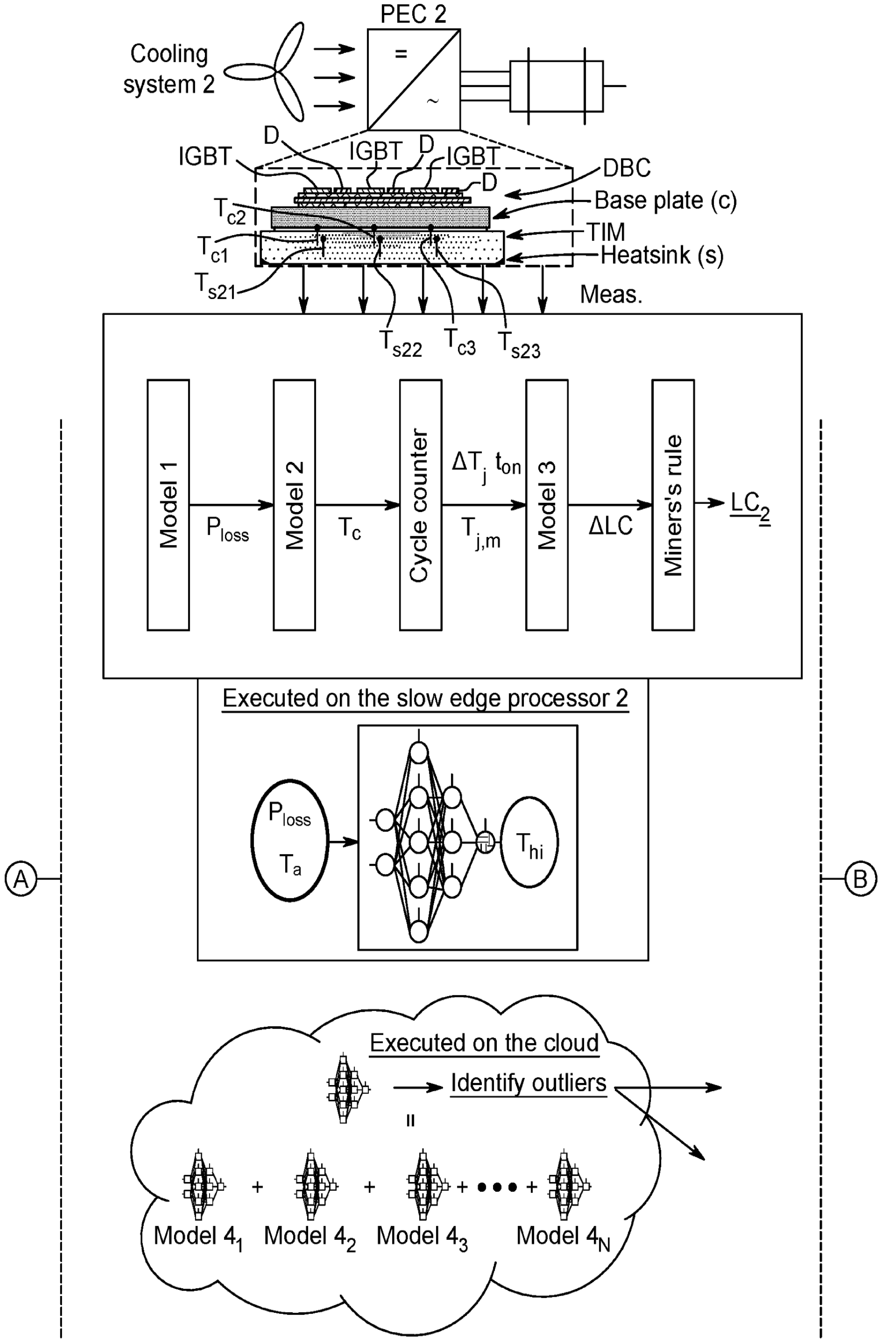
PEC 2
Cooling system 2
=
~
IGBT
D
IGBT
D
IGBT
D
DBC
Base plate (c)
TIM
Heatsink (s)
T_{c2}
T_{c1}
T_{s21}
Meas.
T_{s22}
T_{c3}
T_{s23}
Model 1
P_{loss}
Model 2
T_c
Cycle counter
ΔT_j t_{on}
$T_{j,m}$
Model 3
ΔLC
Miners's rule
LC_2
Executed on the slow edge processor 2
P_{loss}
T_a
T_{hi}
A
B
Executed on the cloud
Identify outliers
=
Model 4_1
Model 4_2
Model 4_3
Model 4_N

FIG. 3B

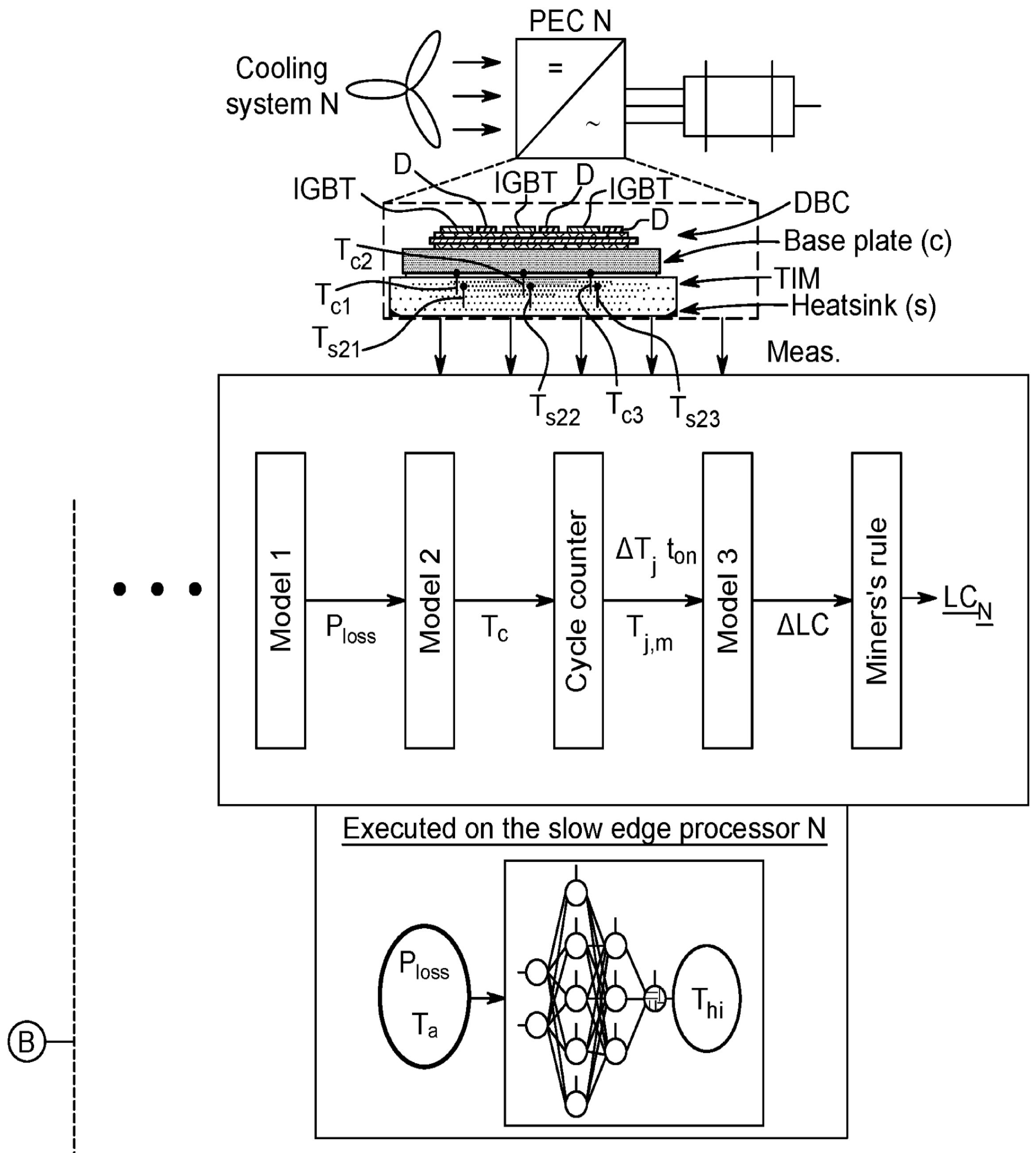
PEC N
Cooling system N
=
~
IGBT
D
IGBT
D
IGBT
D
DBC
Base plate (c)
TIM
Heatsink (s)
Tc2
Tc1
Ts21
Meas.
Ts22
Tc3
Ts23
Model 1
Ploss
Model 2
Tc
Cycle counter
ΔTj ton
Tj,m
Model 3
ΔLC
Miners's rule
LCN
Executed on the slow edge processor N
Ploss
Ta
Thi
B

FIG. 3C

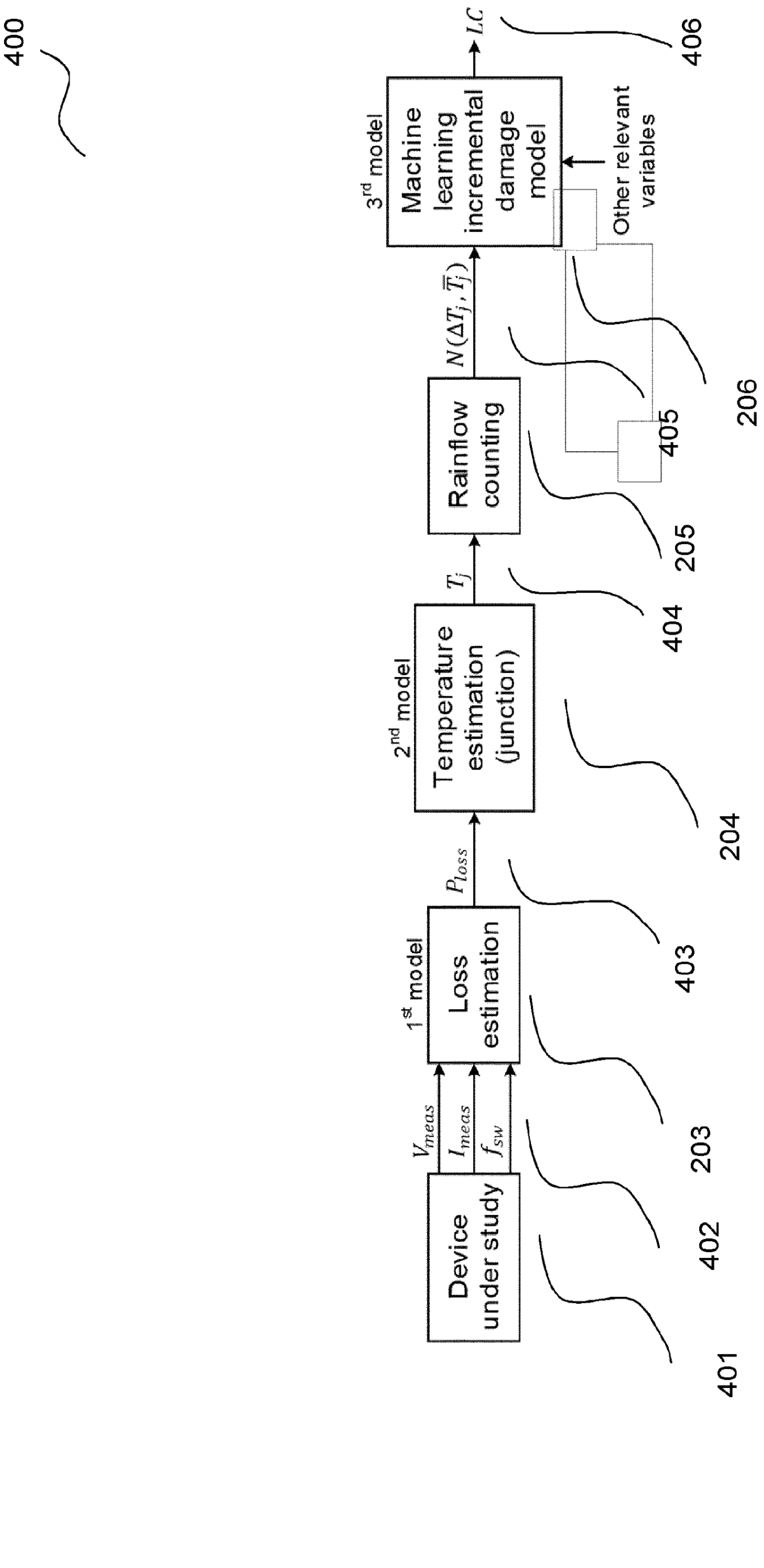
400
Device under study
V_{meas}
I_{meas}
f_{sw}
1st model
Loss estimation
P_{loss}
2nd model
Temperature estimation (junction)
T_j
Rainflow counting
$N(\Delta T_j, \overline{T}_j)$
3rd model
Machine learning incremental damage model
Other relevant variables
LC
401
402
203
403
204
404
205
405
206
406

FIG. 4

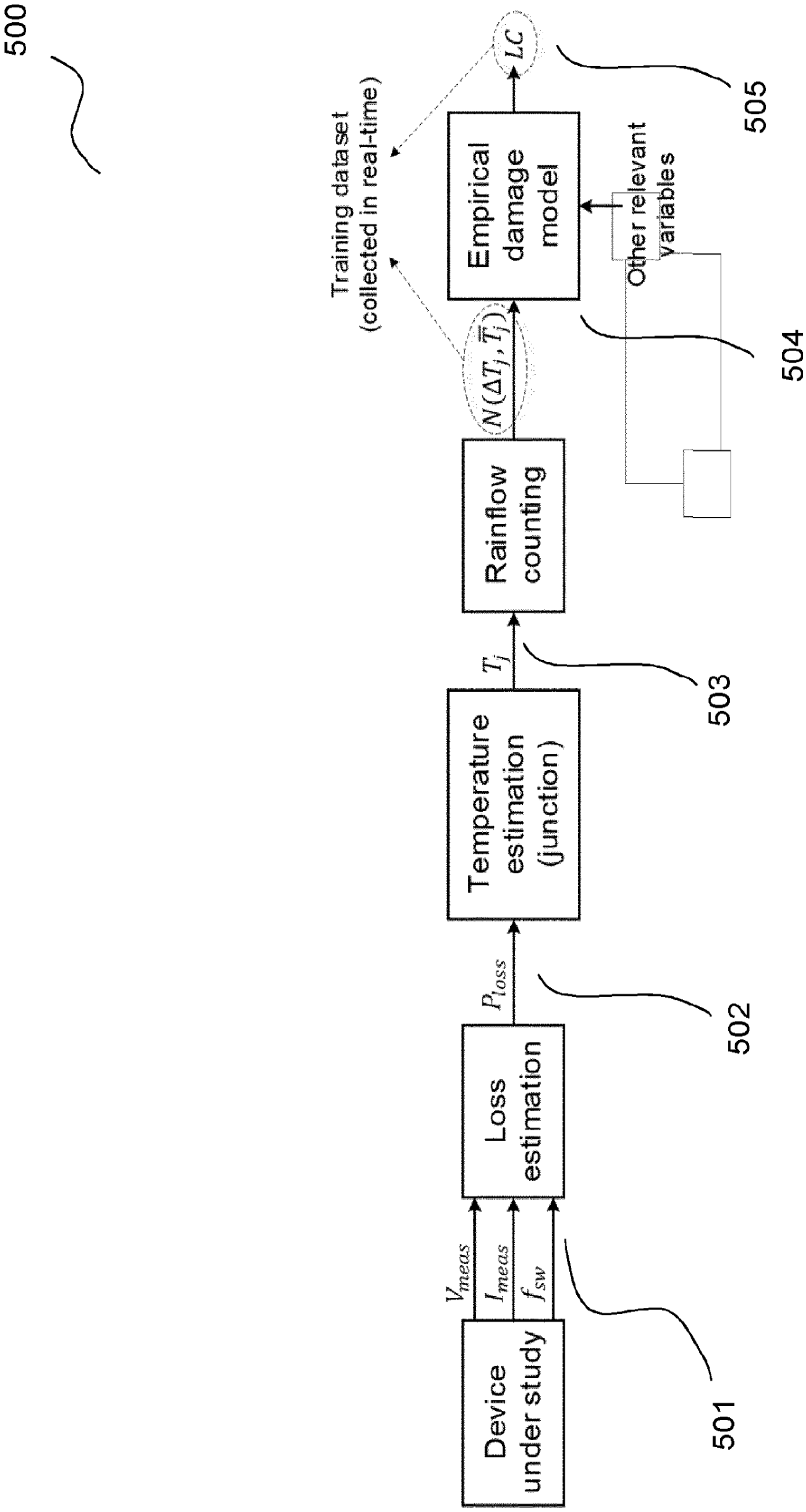
500
Device under study
V_{meas}
I_{meas}
f_{sw}
501
Loss estimation
P_{loss}
502
Temperature estimation (junction)
T_j
503
Rainflow counting
$N(\Delta T_j, \overline{T}_j)$
Empirical damage model
504
Other relevant variables
LC
505
Training dataset (collected in real-time)

FIG. 5

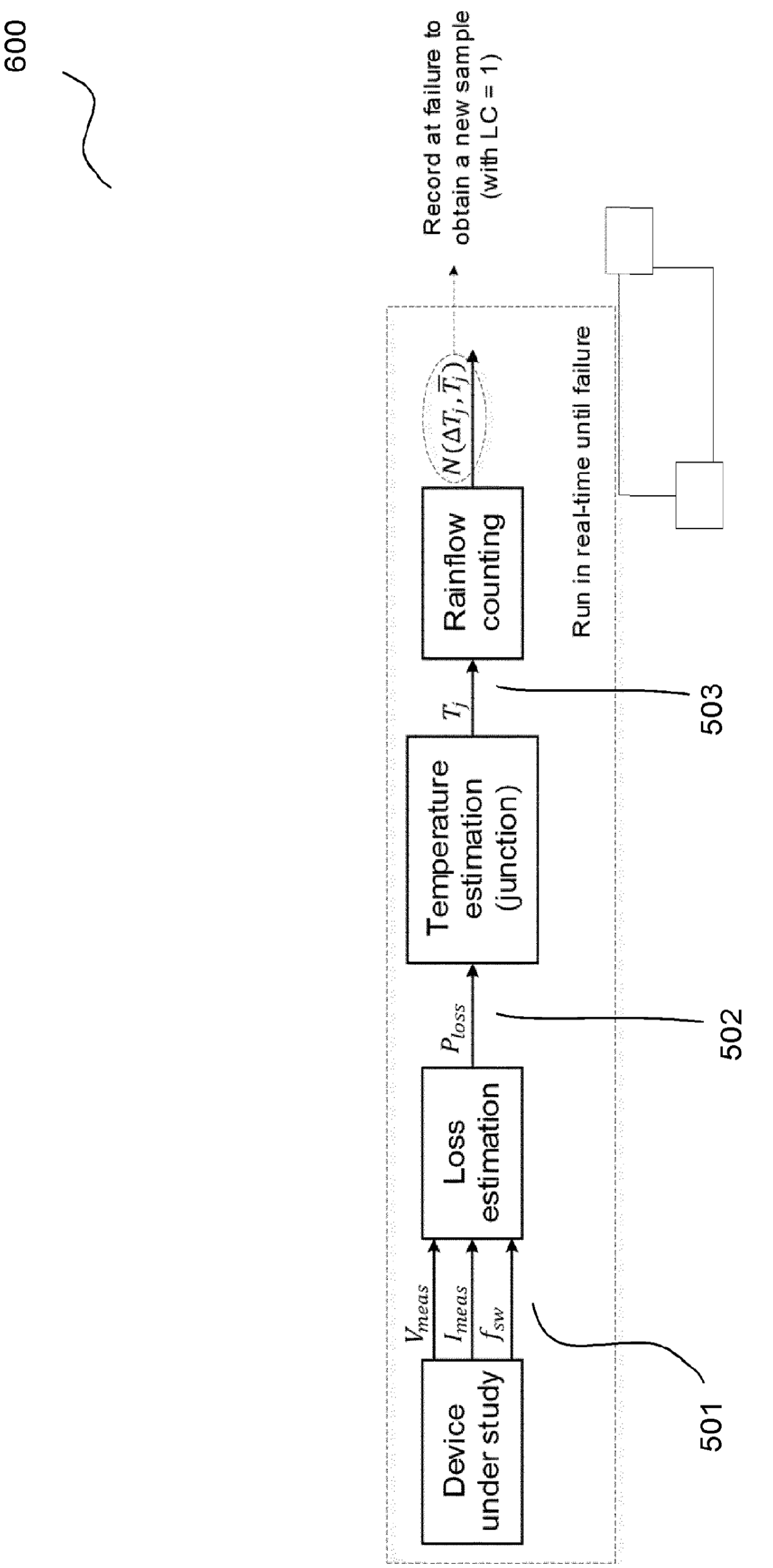
600
Device under study
V_{meas}
I_{meas}
f_{sw}
501
Loss estimation
P_{loss}
502
Temperature estimation (junction)
T_j
503
Rainflow counting
$N(\Delta T_j, \overline{T}_j)$
Record at failure to obtain a new sample (with LC = 1)
Run in real-time until failure

FIG. 6

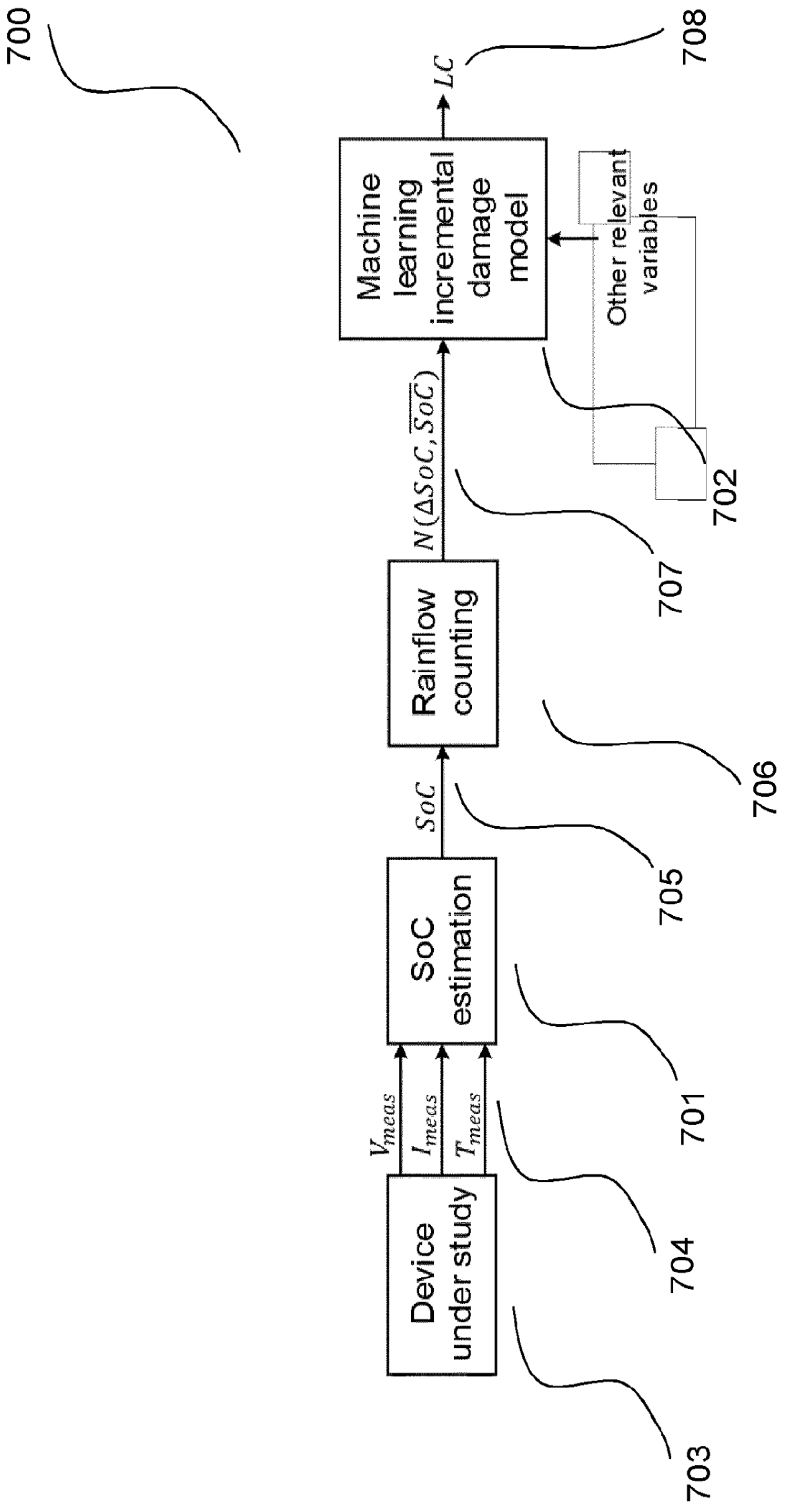
700
Device under study
V_{meas}
I_{meas}
T_{meas}
SoC estimation
SoC
Rainflow counting
$N(\Delta SoC, \overline{SoC})$
Machine learning incremental damage model
Other relevant variables
LC
701
702
703
704
705
706
707
708

FIG. 7

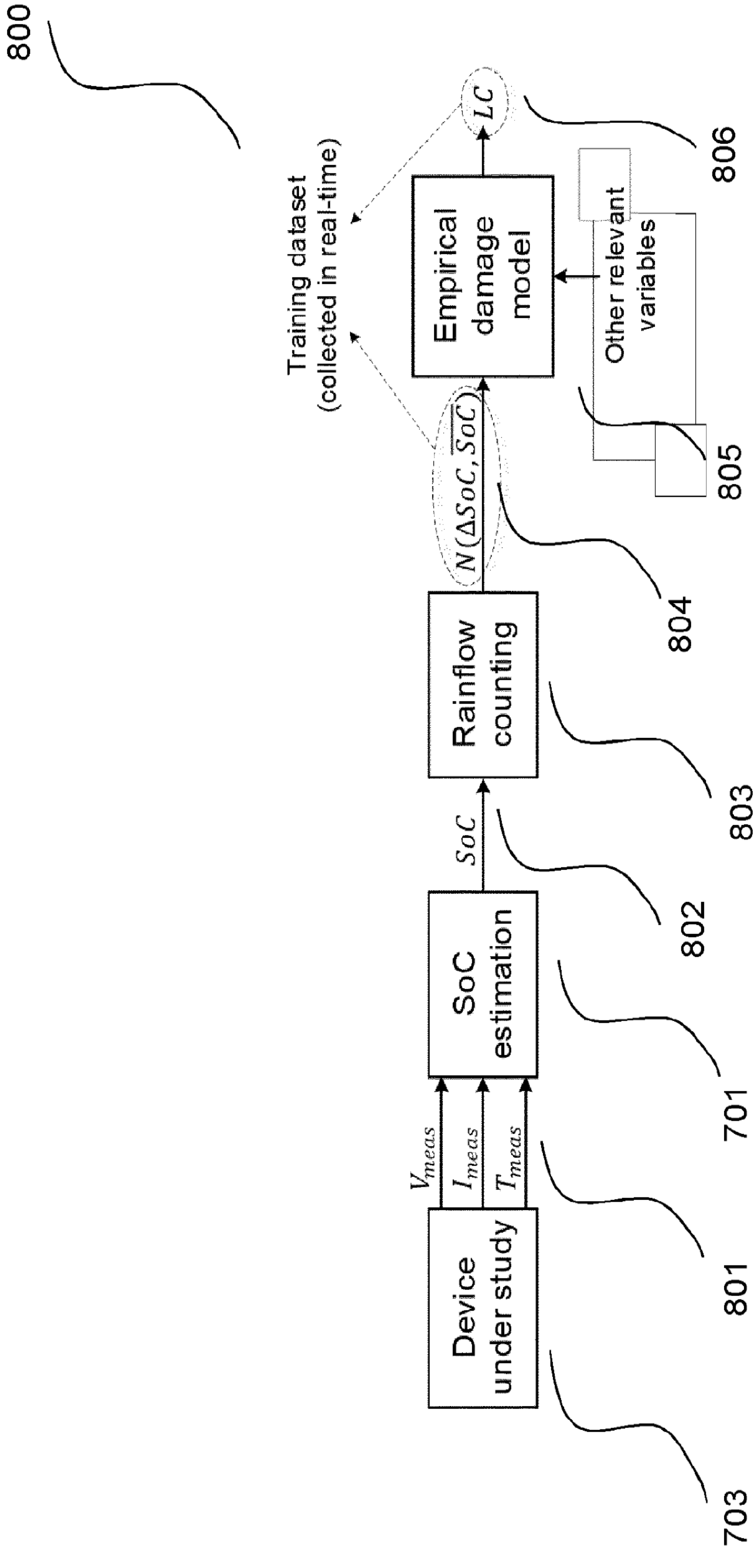
800
Training dataset
(collected in real-time)
Device under study
V_{meas}
I_{meas}
T_{meas}
SoC estimation
SoC
Rainflow counting
$N(\Delta SoC, \overline{SoC})$
Empirical damage model
LC
Other relevant variables
703
801
701
802
803
804
805
806

FIG. 8

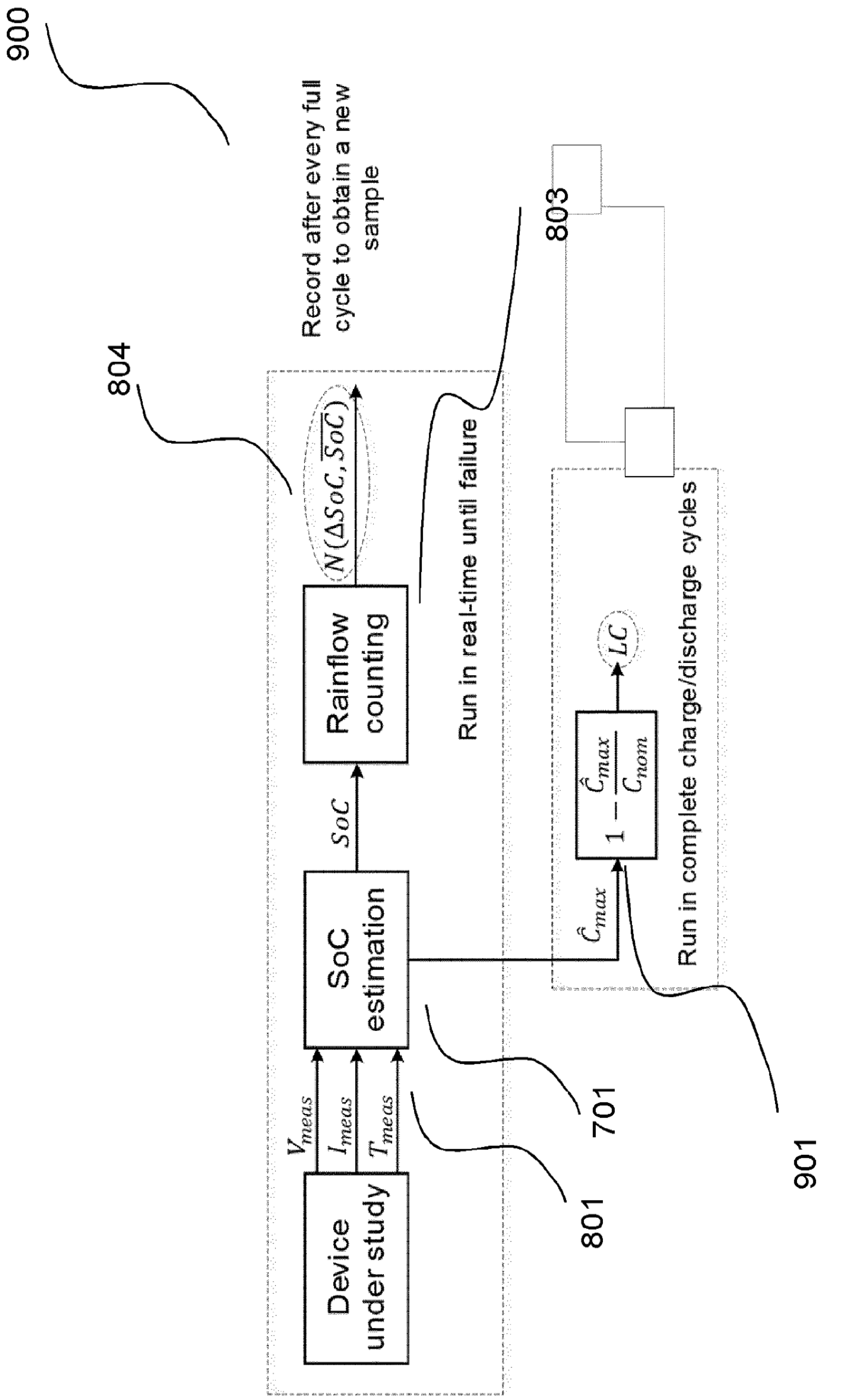
900
Record after every full cycle to obtain a new sample
804
803
$N(\Delta SoC, \overline{SoC})$
Rainflow counting
Run in real-time until failure
SoC
SoC estimation
Device under study
V_{meas}
I_{meas}
T_{meas}
701
801
$\hat{C}_{max}$
$1 - \frac{\hat{C}_{max}}{C_{nom}}$
LC
Run in complete charge/discharge cycles
901

FIG. 9

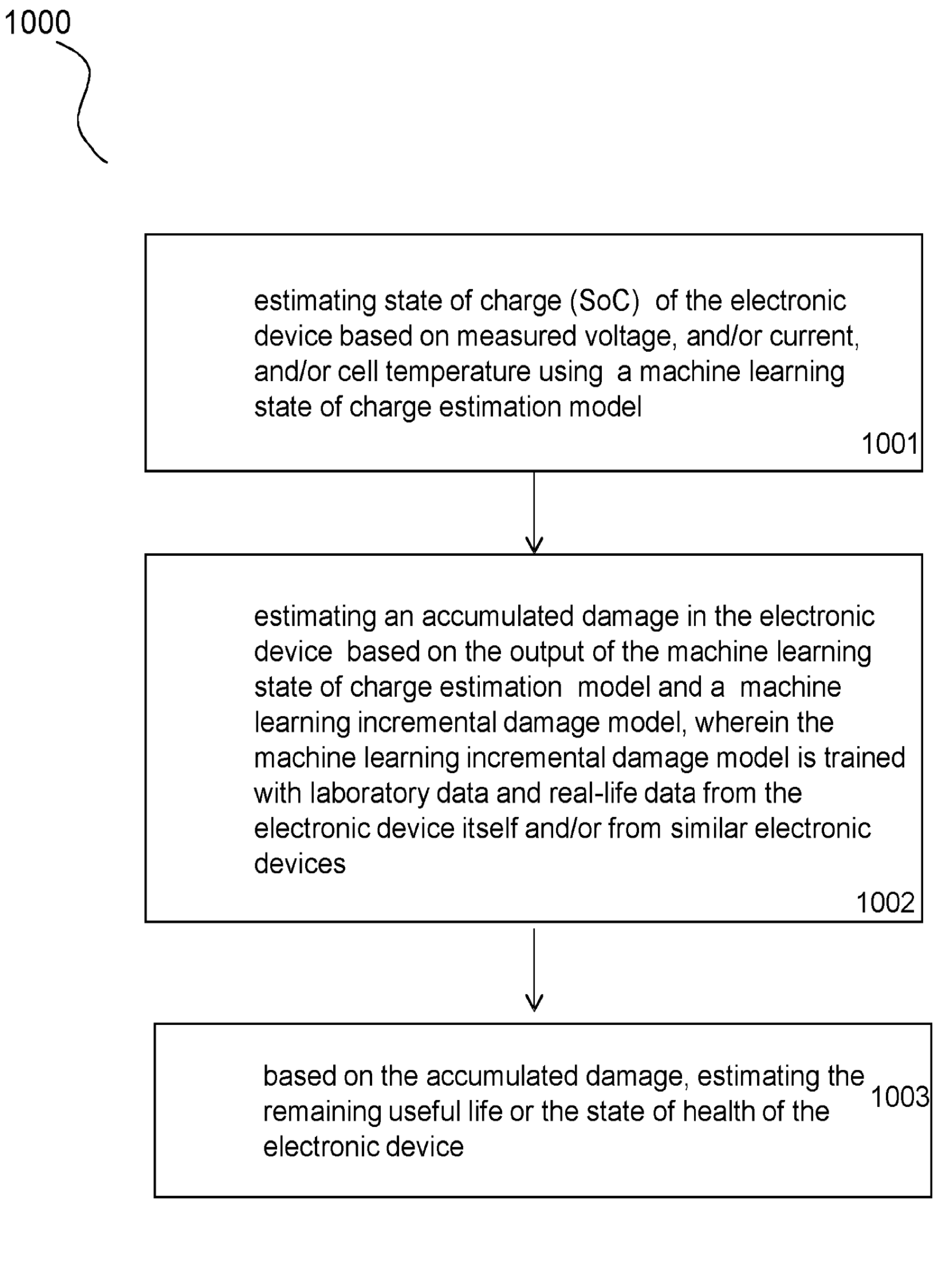
1000
estimating state of charge (SoC) of the electronic device based on measured voltage, and/or current, and/or cell temperature using a machine learning state of charge estimation model
1001
estimating an accumulated damage in the electronic device based on the output of the machine learning state of charge estimation model and a machine learning incremental damage model, wherein the machine learning incremental damage model is trained with laboratory data and real-life data from the electronic device itself and/or from similar electronic devices
1002
based on the accumulated damage, estimating the remaining useful life or the state of health of the electronic device
1003

FIG. 10

INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2022/064158

A. CLASSIFICATION OF SUBJECT MATTER
INV. G01R31/26 G01R31/392
ADD.

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)
G01R G06N

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 3 820 037 A1 (GEN ELECTRIC [US]) 12 May 2021 (2021-05-12)	12-26
A	paragraph [0022] - paragraph [0032]; figure 2B paragraph [0061]	1-11
X	US 2017/276730 A1 (SABATE JUAN ANTONIO [US] ET AL) 28 September 2017 (2017-09-28)	12-26
A	paragraph [0022] - paragraph [0053]; claim 19	1-11

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[x] Further documents are listed in the continuation of Box C. [x] See patent family annex.

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"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance;; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance;; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
18 August 2022	01/09/2022

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

Authorized officer
Meliani, Chafik

2

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	ZHANG ZHONGQING ET AL: "A High-Efficiency IGBT Health Status Assessment Method Based on Data Driven", IEEE TRANSACTIONS ON ELECTRON DEVICES, IEEE, USA, vol. 68, no. 1, 8 December 2020 (2020-12-08), pages 168-174, XP011828197, ISSN: 0018-9383, DOI: 10.1109/TED.2020.3037266 [retrieved on 2020-12-23] II. STRUCTURAL DEGRADATION SIMULATION MODELAND SENSITIVE PARAMETERS -----	1-26
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X A	US 2016/259013 A1 (BASU SUMAN [IN] ET AL) 8 September 2016 (2016-09-08) paragraph [0049] - paragraph [0070]; figure 2 -----	1-11, 22-25 12-21,26
A	DE 10 2019 126245 A1 (PORSCHE AG [DE]) 1 April 2021 (2021-04-01) paragraph [0008] -----	1-26
A	US 5 828 567 A (ERYUREK EVREN [US] ET AL) 27 October 1998 (1998-10-27) figure 5A -----	1-26
A	CN 112 415 414 A (UNIV HANGZHOU DIANZI; UNIV HUZHOU) 26 February 2021 (2021-02-26) paragraph [0003] -----	1-26
A	CN 109 558 681 A (BEIJING ELECTRIC VEHICLE CO LTD) 2 April 2019 (2019-04-02) claims 1-4 -----	1-26
A	CN 110 795 894 A (SHANGHAI G PULSE TECH CO LTD) 14 February 2020 (2020-02-14) claim 1 -----	1-26
A	CN 112 182 981 A (EAST GROUP HENAN CO LTD) 5 January 2021 (2021-01-05) claim 1 -----	1-26
A	EP 1 702 219 A1 (LG CHEMICAL LTD [KR]) 20 September 2006 (2006-09-20) claim 1 -----	1-26
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C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
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2

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No

PCT/EP2022/064158

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			TW	I260808	B	21-08-2006
			US	2005194936	A1	08-09-2005
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CN 108957352	A	07-12-2018	NONE			