Secure and low-traffic federated network based identification of outliers in a population of electronic devices

Dragicevic, Tomislav; Izquierdo, Pere; Enrique Lopez Gajardo, Miguel

Publication date:
2022

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

Citation (APA):
Dragicevic, T., Izquierdo, P., & Enrique Lopez Gajardo, M. (2022). Secure and low-traffic federated network based identification of outliers in a population of electronic devices. (Patent No. *WO2022248535*).

(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 2022/248535 A1

(51) **International Patent Classification:**
G06N 3/04 (2006.01) *G06N 3/08* (2006.01)

(21) **International Application Number:**
PCT/EP2022/064164

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

(25) **Filing Language:** English

(26) **Publication Language:** English

(30) **Priority Data:**
21175716.6 25 May 2021 (25.05.2021) EP

(71) **Applicant: DANMARKS TEKNISKE UNIVERSITET** [DK/DK]; Anker Engelunds Vej 101, 2800 Kongens Lyngby (DK).

(72) **Inventors: DRAGICEVIC, Tomislav**; c/o Danmarks Tekniske Universitet, Anker Engelunds Vej 101, 2800 Kongens Lyngby (DK). **IZQUIERDO, Pere**; c/o Danmarks Tekniske Universitet, Anker Engelunds Vej 101, 2800 Kongens Lyngby (DK). **ENRIQUE LOPEZ GAJARDO, Miguel**; c/o Danmarks Tekniske Universitet, Anker Engelunds Vej 101, 2800 Kongens Lyngby (DK).

(74) **Agent: HØIBERG P/S**; Adelgade 12, 1304 Copenhagen K (DK).

(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:** SECURE AND LOW-TRAFFIC FEDERATED NETWORK BASED IDENTIFICATION OF OUTLIERS IN A POPULATION OF ELECTRONIC DEVICES

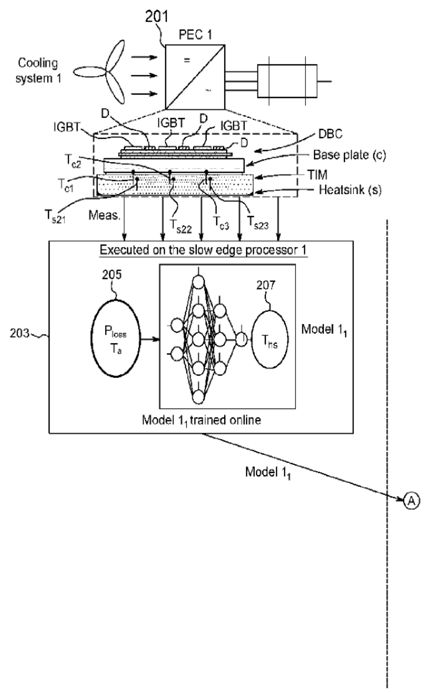


FIG. 2A

(57) Abstract: The invention regards a method for identifying outliers in a population of electronic devices, the method comprising the steps of: providing a plurality of first machine learning models, each first machine learning model associated with one electronic device in a population of electronic devices, wherein each first machine learning model is incrementally trained based on estimated input power loss and/or input ambient temperature and/or output heat sink temperature and/or voltage of each electronic device; providing a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models; and comparing the second machine learning model with each of the first machine learning models to identify outliers among the population and wherein the electronic devices are power converters or power switches or batteries or battery systems used for power applications.

WO 2022/248535 A1

[Continued on next page]

Declarations under Rule 4.17:

— *of inventorship (Rule 4.17(iv))*

Published:

— *with international search report (Art. 21(3))*
— *before the expiration of the time limit for amending the claims and to be republished in the event of receipt of amendments (Rule 48.2(h))*
— *in black and white; the international application as filed contained color or greyscale and is available for download from PATENTSCOPE*

Secure and low-traffic federated network based identification of outliers in a population of electronic devices

The disclosure relates to a method using machine learning for the identification of outliers within a population of electronic devices, in order to be able to identify malfunctioning or harshly used devices. The disclosure further relates to a computing system and a computer program, executed on a computer system, implementing the method.

Background

A huge amount of the electrical energy in the world is used for powering pumps, fans and compressors and similar devices. Furthermore, an increasing amount of electrical energy is used for charging energy storage devices such as capacitors and batteries. Many of these devices are powered by electronic devices, such as power electronic devices, for example power converters.

In addition, the recent focus on green solutions on a greater scale, that will help for the sustainable transformation to limit climate change, is increasing the demand for power electronics and electronic devices such as batteries. Power electronics and electronic devices such as batteries are also widely used in the field of Internet of things (IoT) devices.

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

Among a population of electronic devices, for example power converters, battery cells or semiconductor switches, it is fundamental to be able to identify the malfunctioning electronic devices in order to repair or substitute them in good time and prevent situations where customers are not provided with the underlying service. The presently disclosed patent application addresses this need.

Summary

A first aspect of the present disclosure relates to a method for identifying outliers in a population of electronic devices selected from the group of: power converters, power switches, batteries and battery systems used for power applications, the method comprising the steps of:

- providing a plurality of first machine learning models, each first machine learning model associated with one electronic device in the population of electronic devices, wherein each first machine learning model is incrementally trained based on estimated or measured input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each associated electronic device and/or of one or more of the plurality of electronic devices;
- providing a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models; and
- comparing the second machine learning model with each of the first machine learning models to identify outliers among the population.

In one embodiment, power switches may be power semiconductor switches.

One embodiment of the present disclosure relates to cloud-based electronic devices outlier detection, that is, identification of electronic devices with malfunctioning cooling systems, or the ones that are currently running through particularly lifetime consuming mission profiles.

Electronic or electric devices may be power converters and/or power switches and/or batteries and/or battery systems for power applications.

The method of this disclosure may be computer-implemented.

In one embodiment of the present disclosure, the electronic devices may be power converters or batteries or battery systems used for power applications. In one embodiment of the present disclosure, the electronic devices are dynamical systems with a plurality of sensors, such as power converters, power switches, batteries or battery systems for power applications.

In one embodiment of the present disclosure, detection of outliers within a large population of power electronic converters and devices is based on two machine-learning models, a first model and a second model, functioning in dependence to each other.

The second model may be established as a federated average of a population of first models.

In one embodiment of the present disclosure, outlier power electronic devices may be identified by comparing the outputs of the second model and the outputs of the first model of that particular electronic device for the same inputs, wherein these calculations are partially executed on a comparatively slow edge processor and partially on the cloud, and wherein all first models are trained online. Each one of the plurality of first models is trained directly based on estimated input power loss and/or input ambient temperature and/or output heat sink temperature and/or voltage of each associated electronic device, and/or indirectly on similar data from all or a plurality of electronic devices. That is because the second machine learning model, which is a federated average of the first machine learning models, may send updates of parameters, such as weights and biases, to the first models: in this way, the data coming from all devices influences and optimizes the training of the first models.

In one embodiment of the present application, the method is intended to identify outliers in complex systems, such as power converters or batteries, comprising a plurality of sensors. The presently disclosed method is therefore intended for finding anomalies of dynamic systems, and not only anomalies of single sensors.

In one embodiment of the present disclosure, the following steps may be provided: learning, by training offline or online on an edge processor within or connected to each of the distributed power converters, the mapping from one or more input variables to one or more output variables belonging to a given population; establishing the first model N times, each model for one converter in a given population of N converters; performing, on the cloud, a federated averaging of the N first models in order to provide the second model; identifying outlier(s) by continuously comparing outputs, such as predicted heat sink temperature output temperature, output voltage, output vibration, output capacity, of the current version of the second model with current versions of each of the N first models, when the second model is subjected to the same inputs as a first model, the input comprising one or more incoming measurements and/or estimated variables, such as input power loss, input ambient temperature, input current, input rotating speed, from each of the electronic devices, and wherein this comparison operation can be executed either on the edge processor within or in connection to each distributed converter, or on the cloud.

In one embodiment of the present disclosure an electronic device is identified as an outlier if a deviation between an output predicted by the second machine learning model and an output recorded by one or more of the plurality of first machine learning models, for the same input, or a deviation in a change of weights or biases between the second machine learning model and each of the first machine learning models exceeds a threshold value defined by a user or a calculated threshold value, and wherein the calculated threshold value is calculated based on a selected criterion and/or on input/output data collected during normal and/or anomalous operation of each device associated with a respective model of the plurality of first machine learning models.

In one embodiment of the present disclosure, the first and second models may have same inputs and outputs.

The presently disclosed method may further comprise identifying an electronic device as an outlier based on at least one of criteria selected among: (a) an absolute difference between the first model output and the federated model output exceeds the threshold, (b) an absolute difference between the second model output and corresponding device measurements exceeds the threshold, (c) an absolute difference between the first model output and the corresponding device measurements exceeds a threshold, (d) a mean absolute difference between values of the first model parameters and values of the second model parameters exceeds a threshold, and/or (e) a mean of absolute values of gradients in the first model updates exceeds the threshold; and wherein the threshold is pre-determined or set by a user or calculated based on input/output data collected during normal and/or anomalous operation of the device associated with the plurality of first machine learning models.

Identification of an outlier may therefore be based on a comparison and the use, in most cases, of a threshold. The used values may change depending on the application. The value of the threshold may be set by a user or may be obtained by a calculation, the calculation depending on criteria and based on data collected during normal and/or anomalous operation of the device.

In an embodiment of the presently disclosed application, the first machine learning models may be optionally trained incrementally and substantially in real-time by incoming streaming static or sequence data, and the weights and biases of the first machine learning model are updated after each new input or batch of inputs is presented.

In the disclosed method, the second model may be configured to assume that the majority of the electric devices is functioning normally and a minority of outliers is to be identified.

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 disclosed method.

The present disclosure further relates to a computing system for identifying outliers in a population of electronic devices selected from the group of: power converters, power switches, batteries and battery systems used for power applications, comprising:

- a plurality of edge processors each residing in, or in connection to, each of the electronic devices, wherein each of the edge processors comprises a first machine learning model incrementally trained on the edge processor based on estimated or measured input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each associated electronic device and/or of one or more of the plurality of electronic devices; and
- an external computing device configured to provide a second machine learning model, the second machine learning model being based on a

federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models;

wherein each of the edge processors and/or the external computing device are configured to perform a comparison between the first model and the second model and wherein the external computing device is configured to identify outliers among the population, using the result of each of the comparisons.

.

In one embodiment of this disclosure, the plurality of edge processors and the external computing device may communicate via a communication link, such as a wireless communication link.

The present disclosure further relates to a cloud system for identifying outliers in a population of electronic devices selected from the group of: power converters, power switches, batteries and battery systems used for power applications, the system comprising a remote processor, the remote processor providing:

- a plurality of first machine learning models, each corresponding to one of the electronic devices, wherein each of the first machine learning models is incrementally trained based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each electronic device; and
- a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models,

wherein the remote processor is configured to identify outliers among the population of electronic devices, based on a comparison between each of the plurality of first machine learning models and the second machine learning model.

The present disclosure further relates to an edge processor comprising a machine learning model, wherein the machine learning model is trained incrementally and substantially at real-time by incoming streaming static or sequence data related to the estimated input loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of an electronic device, and wherein the weights and biases of the model are updated after each new input or batch of inputs is presented.

A person skilled in the art will recognize that the presently disclosed method for identifying outliers in a population of electronic devices, such as power converters and/or batteries, may be performed using any embodiment of any of the presently disclosed systems.

The presently disclosed method may be applied in different ambient or seasonal conditions.

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 disclosed method.
Fig. 2 shows a schematic view of an embodiment of a computing system (200) for identifying outliers in a population (201) of electronic devices.

Detailed description

The present disclosure relates to a method for identifying outliers in a population of electronic devices, the method comprising the steps of:

- providing a plurality of first machine learning models;
- providing a second machine learning model; and
- comparing the second machine learning model with each of the first machine learning models to identify outliers among the population.

Preferably each first machine learning model is associated with one electronic device in the population of electronic devices, wherein each first machine learning model is incrementally trained based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or voltage and/or output vibration level and/or output capacity of each electronic device; and the second machine learning model may be based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models.

In one embodiment of the present disclosure the first models may have as input: input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period. The sampling period may be non-constant and depends on application and may therefore be an input variable. For example, if a parameter remains constant over a long period of time, for example a user-defined speed reference, it may not be logged at a high frequency, such as a log for, for example, a motor current. Rotating speed may be, for example, rotating speed of a fan, such as a cooling fan.

In one embodiment of the present disclosure the first models may have as output: output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity. Capacity as an output is relevant if the electronic device is a battery or a battery system. Other output variables are relevant for, for example, power converters.

The second model, which may be a federated average of the plurality of first models, may have the same input and output variables as the first models it is based upon.

Fig. 1 shows a schematic view of an embodiment of the disclosed method. (100) for identifying outliers in a population of electronic devices, the method comprising the steps of: (101) providing a plurality of first machine learning models, (102) providing a second machine learning model and (103) comparing the second machine learning model with each of the first machine learning models..

The population of electronic devices may comprise an arbitrary number of electronic devices, such as at least 10 or at least 100 electronic devices, or at least 1000 electronic devices, or at least one million electronic devices.

In one embodiment of the present disclosure, the following steps may be provided: learning, by training offline or online on an edge processor within or connected to each of the distributed electronic devices, the mapping from estimated or measured power electronic converter losses and/or ambient temperature and/or input current and/or input rotating speed and/or input sampling period to the measured heat sink temperature and/or output voltage and/or output vibration level and/or output capacity in each electronic device belonging to a given population; establishing the first model N times, each model for one device in a given population of N devices; performing, on the cloud, a federated averaging of the N first models in order to provide the second model; identifying outlier(s) by continuously comparing outputs, such as predicted heat sink temperature and/or predicted voltage and/or predicted vibration level and/or predicted capacity, of the current version of the second model with current versions of each of the N first models, when the second model is subjected to the same inputs as a first model, the input comprising incoming measurements, such as estimated power losses and/or measured ambient temperature and/or input current and/or input rotating speed and/or input sampling period, from the each of the electronic devices, and wherein this comparison operation can be executed either on the edge processor within or in connection to each distributed device, or on the cloud.

In one embodiment of the present disclosure, each of the first machine learning models and the second machine learning model may have inputs, such as input power loss and/or input ambient temperatures and/or input current and/or input sampling time period, and outputs, such as output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity, and parameters, such as weights and biases.

In one embodiment of the present disclosure, the step of comparing the second machine learning model with each of the first machine learning models comprises comparing parameters of the second machine learning model to parameters of the first models.

In a further embodiment of the present disclosure, the method may comprise the step of comparing the output of the second machine learning model to the output of the first models, such as heat sink temperature and/or voltage and/or output voltage and/or output vibration level and/or output capacity.

In a further embodiment, an outlier in the population of electronic devices may be identified if a deviation between an output predicted by the second machine learning model and an output recorded by one or more of the plurality of first machine learning models, for the same input, or a deviation in the change of weights or biases between the second machine learning model and each of the first machine learning models exceeds a threshold value defined by a user or a calculated threshold value.

In an embodiment of the present disclosure, the output recorded by one or more of the plurality of first machine learning models may be the heat sink temperature and/or output voltage and/or output vibration level and/or output capacity and/or another relevant health variable, and wherein the input of the plurality of first machine learning models may be the estimated loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period.

In one embodiment of the present disclosure the output predicted by the second machine learning model is a second heat sink temperature and/or output voltage and/or output vibration level and/or output capacity and/or another relevant health variable, and wherein the input of the second machine learning model is the same as the input of the compared first machine learning model.
The output of the machine learning models may be filtered with a low-pass filter.

In one embodiment, the data sent from the first machine learning models to the second machine learning model may be compressed and encrypted, wherein the compression and encryption is obtained as a consequence of the non-interpretability of the first machine learning model parameters, and wherein compression and encryption do not require any additional steps in the computations, and wherein the first machine learning models may send the parameters of the first machine learning models to the second machine learning model, wherein the parameters, such as weights and biases, may not be interpreted directly by a potential third party intruder and may constitute a limited amount of data to be sent.

In another embodiment, data sent from the first machine learning models to the second machine learning mode may be further compressed and encrypted by use of an additional compression and encryption algorithm.

In one embodiment of the present disclosure, the data sent from the first machine learning models to the second machine learning model are the input, such as the power loss and the ambient temperature, and/or the output, such as the heat sink temperature and/or the voltage, and/or the parameters of the first machine learning models, such as biases and weights.

In one embodiment, data sent from the first machine learning models are biases and weights. Additionally, data pertaining to the device, such as inputs and/or outputs of the first machine learning models, may also be sent.

The data transfer from each of the first machine learning models and the second machine learning model may occur at time intervals or it may occur based on triggering events.

First Model

The first machine learning model may be trained incrementally online by the incoming streaming static or sequence data, such as estimated power, converter loss and/or ambient temperature and/or input current and/or input rotating speed and/or input sampling period as inputs and measured heat sink temperature and/or output voltage and/or output vibration level and/or output capacity as output.

The first machine learning model may be trained incrementally in the sense that the weights and biases of the neural network are updated after each new input or input batch is presented.

Since the heat sink temperature or relevant output variables may typically be static (e.g. vibration) or have time constants in range of seconds to minutes (e.g. heat sink temperatures), the training of the first model may be executed on a slow processor and thereby the overruns caused by the computationally moderately intensive online learning algorithm may be avoided.

In one embodiment of the present application, the first machine learning models may be trained incrementally and substantially in real-time by incoming streaming static or sequence data, and wherein the weights and biases of the first machine learning model are updated after each new input or batch of inputs is presented.

In one embodiment of the present disclosure, the computations of the first machine learning model are executed on an edge computer residing in the electronic device or in connection to the electronic device.

In another embodiment of the present disclosure, the first machine learning model is trained on an edge computer within or in connection to the electronic device and the evaluations of the first model are executed in a remote computer, such as a cloud computer. Evaluations mean running the model to obtain outputs for a set of inputs.

Second Model

The second machine learning model may be updated online on the cloud by continually performing a federated averaging operation of N first models, wherein N is the number of electronic devices in the population of electronic devices.

Assuming that the majority of power electronic converters in the population operate normally and that, for example, the cooling is operating properly and that the ongoing mission profile do not cause excessive damage, the purpose of the second model is to average the predictions of all the distributed first models and thus provide a basis for checking whether any of the distributed electronic devices behaves significantly differently from what the second model predicts, wherein the level of significance may be established by the end-user with the use of a threshold value. Such differences form the basis for identifying outliers in the electronic device population, as also illustrated in fig. 2, where the comparison is carried out, as an example, on the heat sink temperature. For instance, fig. 2 illustrates the situation where the outlier detection is carried out by directly comparing the output of the second model with the current heat sink measurement and/or output voltage and/or output vibration level and/or output capacity and checking the threshold condition. Detection may also be carried out by comparing the output of the second model with the output of each distributed first models and checking the threshold condition for each distributed electronic device. Moreover these comparisons may be carried out either on the edge or in the cloud.

The comparison process may be configured to assume that the majority of the electronic devices is functioning normally and a minority of outliers is to be identified.

The computations of the second machine learning model may be executed on an external computing device, wherein the external computing device may be located remotely in a cloud system.

System

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 disclosed method.

In addition, the present disclosure further relates to a computing system for identifying outliers in a population of electronic devices, comprising:

- a plurality of edge processors each residing in, or in connection to, each of the electronic devices, wherein each of the edge processors comprises a machine learning model incrementally trained on the edge processor based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each associated electronic device and/or of one or more of the plurality of electronic devices; and
- an external computing device configured to provide a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models;

wherein each of the edge processors and/or the external computing device are configured to perform a comparison between the first model and the second model and wherein the external computing device is configured to identify outliers among the population, using the result of each of the comparisons and wherein the electronic devices are power converters or power switches or batteries or battery systems used for power applications.

In the computing system for identifying outliers in a population of electronic devices, the plurality of edge processors and the external computing device may communicate via a communication link, such as a wireless communication link.

Fig. 2 shows a schematic view of an embodiment of a computing system (200) for identifying outliers in a population (201) of electronic devices, comprising a plurality of edge processors each residing in, or in connection to, each of the electronic devices, wherein each of the edge processors comprises a first machine learning model (203), wherein the first machine learning models have inputs (205) such as ambient temperature and/or estimated power loss and outputs (207) such as heat sink temperature, the computing system also comprising an external computing device configured to provide a second machine learning model (204) being based on a federated average of model parameters of a plurality of first machine learning models.

The present disclosure further relates to a cloud system for identifying outliers in a population of electronic devices, comprising a remote processor, the remote processor providing:

- a plurality of first machine learning models, each corresponding to one of the electronic devices, wherein each of the first machine learning models is incrementally trained based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each electronic device; and
- a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models,

wherein the remote processor is configured to identify outliers among the population of electronic devices, based on a comparison between each of the plurality of first machine learning models and the second machine learning model and wherein the electronic devices are power converters or power switches or batteries or battery systems used for power applications.

The cloud system for identifying outliers in a population of electronic devices may communicate to a plurality of edge processors, wherein each of the first machine learning models is trained on one of the plurality of edge processors.

The present disclosure further relates to an edge processor comprising a machine learning model, wherein the machine learning model is trained incrementally and substantially in real-time based on incoming streaming static or sequence data related to the estimated input loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of an electronic device, and wherein the weights and biases of the model are updated after each new batch of inputs is presented.

Further details

1. A method for identifying outliers in a population of electronic devices, the method comprising the steps of:
    - providing a plurality of first machine learning models, each first machine learning model associated with one electronic device in the population of electronic devices, wherein each first machine learning model is incrementally trained based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or voltage and/or output vibration level and/or output capacity of each electronic device;
    - providing a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models; and
    - comparing the second machine learning model with each of the first machine learning models to identify outliers among the population.

2. The method according to item 1, wherein the population of electronic devices comprises an arbitrary number of electronic devices, such as at least 10 or at

least 100 electronic devices, or at least 1000 electronic devices, or at least one million electronic devices.

3. The method according to any one of the preceding items, wherein the first machine learning models are trained incrementally and in substantially real-time by incoming streaming static or sequence data, and wherein the weights and biases of the first machine learning model are updated after each new input or batch of inputs is presented.

4. The method according to any one of the preceding items, wherein the second model is configured to assume that the majority of the power converters is functioning normally and a minority of outliers is to be identified.

5. The method according to any one of the preceding items, wherein each of the first machine learning models and the second machine learning model have inputs, such as power loss and/or ambient temperatures, and outputs, such as heat sink temperature and/or voltage, and parameters, such as weights and biases.

6. The method according to any one of the preceding items, comprising the step of comparing the federated average of the parameters of the second machine learning model to the parameters of the first models.

7. The method according to any one of the preceding items, comprising the step of comparing the output of the second machine learning model to the output of the first models, such as heat sink temperature and/or voltage.

8. The method according to any one of the preceding items, further comprising the step of identifying an electronic device as an outlier if a deviation between an output predicted by the second machine learning model and an output recorded by one or more of the plurality of first machine learning models, for the same input, or a deviation in the change of weights or biases between the second machine learning model and each of the first machine learning models exceeds a threshold value defined by a user or a calculated threshold value.

9. The method according to item 8, wherein the output recorded by one or more of the plurality of first machine learning models is the heat sink temperature and/or

another relevant health variable such as voltage, and wherein the input of the plurality of first machine learning models is the estimated loss and/or input ambient temperature.

10. The method according to any one of items 8-9, wherein the output predicted by the second machine learning model is a second heat sink temperature and/or another relevant health variable such as voltage, and wherein the input of the second machine learning model is the same as the input of the compared first machine learning model.

11. The method according to any one of the preceding items, wherein the outputs of the machine learning models are filtered with a low-pass filter.

12. The method according to any one of the preceding items, wherein the computations of the first machine learning model are executed on an edge computer residing in the electronic device or in connection to the electronic device.

13. The method according to any one of items 1-11, wherein the first machine learning model is trained on an edge computer within or in connection to the electronic device and wherein the evaluations of the first model are executed in a remote computer, such as a cloud computer.

14. The method according to any one of the preceding items, wherein the computations of the second machine learning model are executed on an external computing device, and wherein the external computing device is located remotely in a cloud system.

15. The method according to any one of the preceding items, wherein data sent from the first machine learning models to the second machine learning model is compressed and encrypted, wherein the compression and encryption is obtained as a consequence of the non-interpretability of the first machine learning model parameters, and wherein compression and encryption do not require any additional steps in the computations.

16. The method according to any one of the preceding items, wherein the data sent from the first machine learning models to the second machine learning model are the input, such as the power loss and the ambient temperature, and/or the

output, such as the heat sink temperature and/or the voltage, and/or the parameters of the first machine learning models, such as biases and weights.

17. The method according to any one of the preceding items, wherein the data transfer from each of the first machine learning models and the second machine learning model occurs at time intervals or it occurs based on triggering events.

18. 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 the preceding items

19. A computing system for identifying outliers in a population of electronic devices, comprising:
    - a plurality of edge processors each residing in, or in connection to, each of the electronic devices, wherein each of the edge processors comprises a first machine learning model incrementally trained on the edge processor based on estimated input power loss and/or input ambient temperature and/or output heat sink temperature of each electronic device; and
    - an external computing device configured to provide a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models;

    wherein each of the edge processors and/or the external computing device are configured to perform a comparison between the first model and the second model and wherein the external computing device is configured to identify outliers among the population, using the result of each of the comparisons.

20. The system according to item 19, wherein the plurality of edge processors and the external computing device communicate via a communication link, such as a wireless communication link.

21. A cloud system for identifying outliers in a population of electronic devices, comprising:
    - a plurality of first machine learning models, each corresponding to one of the electronic devices, wherein each of the first machine learning

models is incrementally trained based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each electronic device; and

- a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models,

the cloud system further comprising a remote processor configured to identify outliers among the population of electronic devices, based on a comparison between each of the plurality of first machine learning models and the second machine learning model.

22. The cloud system according to item 21, wherein the cloud system communicates to a plurality of edge processors, wherein each of the first machine learning models is trained on one of the plurality of edge processors.

23. An edge processor comprising a machine learning model, wherein the machine learning model is trained incrementally and in substantially real-time by incoming streaming static or sequence data related to the estimated input loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of an electronic device, and wherein the weights and biases of the model are updated after each new batch of inputs is presented.

Claims

1. A computer-implemented method for identifying outliers in a population of electronic devices selected from the group of: power converters, power switches, batteries and battery systems used for power applications, the method comprising the steps of:
   - providing a plurality of first machine learning models, each first machine learning model associated with one electronic device in the population of electronic devices, wherein each first machine learning model is incrementally trained based on estimated or measured input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each associated electronic device and/or of one or more of the plurality of electronic devices;
   - providing a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models; and
   - comparing the second machine learning model with each of the first machine learning models to identify outliers among the population.

2. The method according to claim 1, wherein the population of electronic devices comprises an arbitrary number of electronic devices, such as at least 10 or at least 100 electronic devices, or at least 1000 electronic devices, or at least one million electronic devices.

3. The method according to any one of the preceding claims, wherein an electronic device is identified as an outlier if a deviation between an output predicted by the second machine learning model and an output recorded by one or more of the plurality of first machine learning models, for the same input, or a deviation in a change of weights or biases between the second machine learning model and each of the first machine learning models exceeds a threshold value defined by a user or a calculated threshold value, and wherein the calculated threshold value is calculated based on a selected criterion and/or

on input/output data collected during normal and/or anomalous operation of the devices associated with the plurality of first machine learning models or similar devices.

4. The method according to any one of the preceding claims, wherein the first machine learning models are trained offline or incrementally and in substantially real-time by an incoming stream of static or sequence data, and wherein weights and biases of the first machine learning model are updated after each new input or batch of inputs is presented.

5. The method according to any one of the preceding claims, wherein each of the first machine learning models and the second machine learning model have inputs, such as input power loss and/or input ambient temperature and/or input current and/or input sampling time period, and outputs, such as output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity, and parameters, such as weights and biases.

6. The method according to any one of the preceding claims, wherein the step of comparing the second machine learning model with each of the first machine learning models comprises comparing parameters of the second machine learning model to parameters of the first models.

7. The method according to any one of the preceding claims, wherein the step of comparing the second machine learning model with each of the first machine learning models comprises comparing the output of the second machine learning model to the output of the first models, such as heat sink temperature and/or voltage and/or output vibration level and/or output capacity.

8. The method according to any one of the preceding claims, further comprising identifying an electronic device as an outlier if a deviation between an output predicted by the second machine learning model and an output recorded by one or more of the plurality of first machine learning models, for the same input, or a deviation in the change of weights or biases between the second machine learning model and each of the first machine learning models exceeds a threshold value defined by a user or a calculated threshold value.

9. The method according to claim 8, wherein the output recorded by one or more of the plurality of first machine learning models is the heat sink temperature and/or voltage and/or vibration level and/or capacity, and wherein the input of the plurality of first machine learning models is the estimated power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling time period.

10. The method according to any one of the preceding claims, further comprising identifying an electronic device as an outlier based on at least one of the criteria selected among: (a) an absolute difference between first model output and federated model output exceeds a threshold, (b) an absolute difference between second model output and corresponding device measurements exceeds a threshold, (c) an absolute difference between first model output and corresponding device measurements exceeds a threshold, (d) a mean absolute difference between values of the first model parameters and values of the second model parameters exceeds a threshold, and/or (e) a mean of absolute values of gradients in the first model updates exceeds a threshold; and wherein the threshold is pre-determined or set by a user or calculated based on input/output data collected during normal and/or anomalous operation of the devices associated with the plurality of first machine learning models or similar devices.

11. The method according to any one of claims 8-9, wherein the output predicted by the second machine learning model is a second heat sink temperature and/or another relevant health variable such as voltage, and wherein the input of the second machine learning model is the same as the input of the compared first machine learning model.

12. The method according to any one of the preceding claims, wherein computations of the first machine learning model are executed on an edge computer residing in the electronic device associated with each of the first machine learning models or in connection to the electronic device.

13. The method according to any one of the preceding claims, wherein data sent from the first machine learning models to the second machine learning model is compressed and encrypted, wherein the compression and encryption is obtained as a consequence of the non-interpretability of first machine learning

model parameters, and wherein compression and encryption do not require any additional steps in the computations.

14. A computer program having instructions which, when executed by a computing device, cause the computing device to carry out the method according to any one of the preceding claims, or when executed by or computing system cause the computing system to carry out the method according to any one of the preceding claims.

15. A computing system for identifying outliers in a population of electronic devices selected from the group of: power converters, power switches, batteries and battery systems used for power applications, the computing system comprising:
   - a plurality of edge processors each residing in, or in connection to, each of the electronic devices, wherein each of the edge processors comprises a first machine learning model incrementally trained on the edge processor based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each associated electronic device and/or of one or more of the plurality of electronic devices; and
   - an external computing device configured to provide a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models;

   wherein each of the edge processors and/or the external computing device are configured to perform a comparison between the first model and the second model and wherein the external computing device is configured to identify outliers among the population, using the result of each of the comparisons.

16. A cloud system for identifying outliers in a population of electronic devices selected from the group of: power converters, power switches, batteries and battery systems used for power applications, the cloud system comprising:
   - a plurality of first machine learning models, each corresponding to one of the electronic devices, wherein each of the first machine learning models is incrementally trained based on estimated input power loss

and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each electronic device; and

- a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models,

the cloud system further comprising a remote processor configured to identify outliers among the population of electronic devices, based on a comparison between each of the plurality of first machine learning models and the second machine learning model.

17. An edge processor comprising a machine learning model, wherein the machine learning model is trained incrementally and in substantially real-time by incoming streaming static or sequence data related to the estimated input loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of an electronic device, and wherein the weights and biases of the model are updated after each new batch of inputs is presented, and wherein the electronic device is a power converter or a power switch or a battery or a battery system used for power applications.

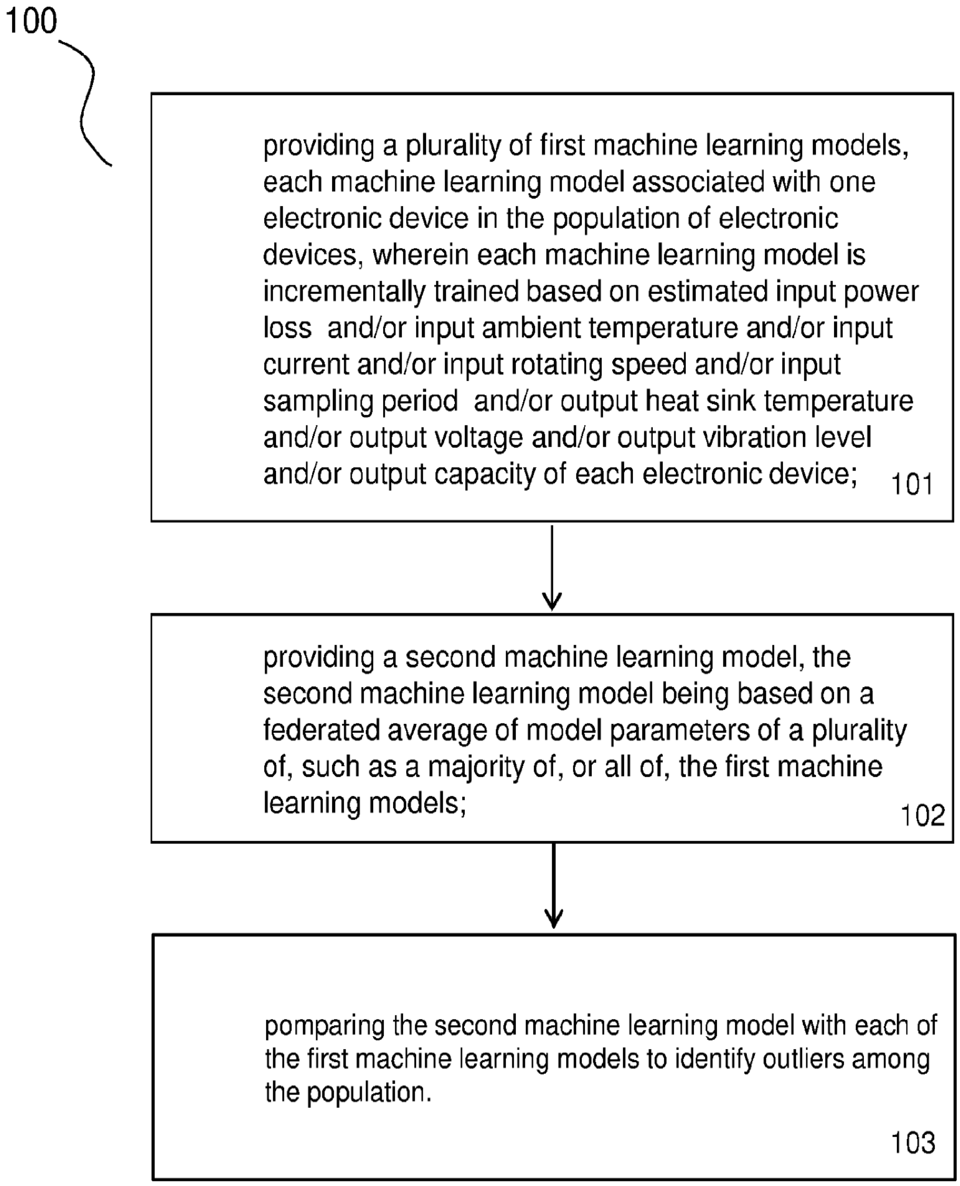
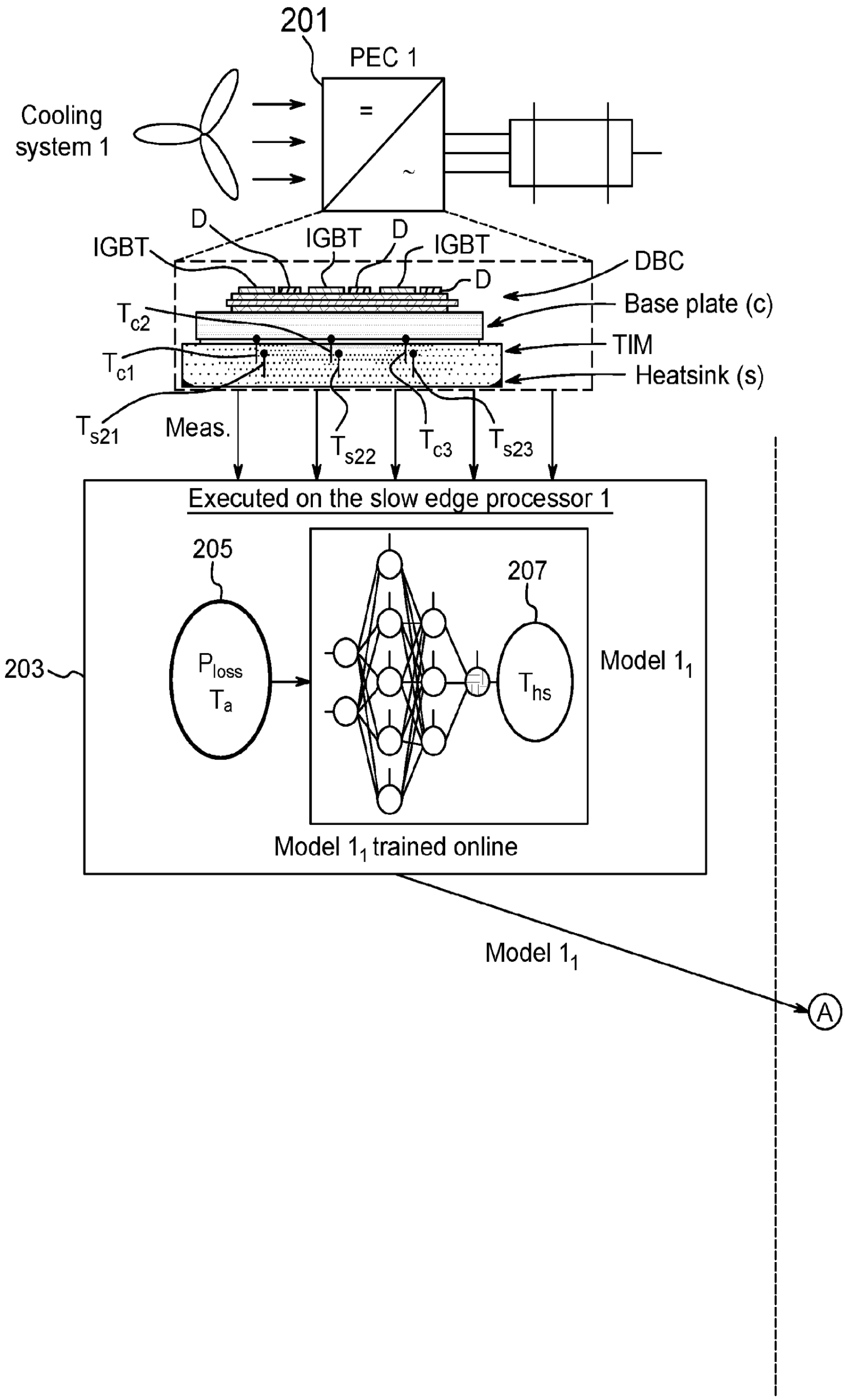

100
providing a plurality of first machine learning models, each machine learning model associated with one electronic device in the population of electronic devices, wherein each machine learning model is incrementally trained based on estimated input power loss and/or input ambient temperature and/or input current and/or input rotating speed and/or input sampling period and/or output heat sink temperature and/or output voltage and/or output vibration level and/or output capacity of each electronic device;
101
providing a second machine learning model, the second machine learning model being based on a federated average of model parameters of a plurality of, such as a majority of, or all of, the first machine learning models;
102
pomparing the second machine learning model with each of the first machine learning models to identify outliers among the population.
103

FIG. 1



201
PEC 1
=
~
Cooling system 1
D
IGBT
IGBT
D
IGBT
DBC
D
Base plate (c)
T_{c2}
TIM
T_{c1}
Heatsink (s)
T_{s21}
Meas.
T_{s22}
T_{c3}
T_{s23}
Executed on the slow edge processor 1
205
207
203
P_{loss}
T_a
T_{hs}
Model 1_1
Model 1_1 trained online
Model 1_1
A

FIG. 2A

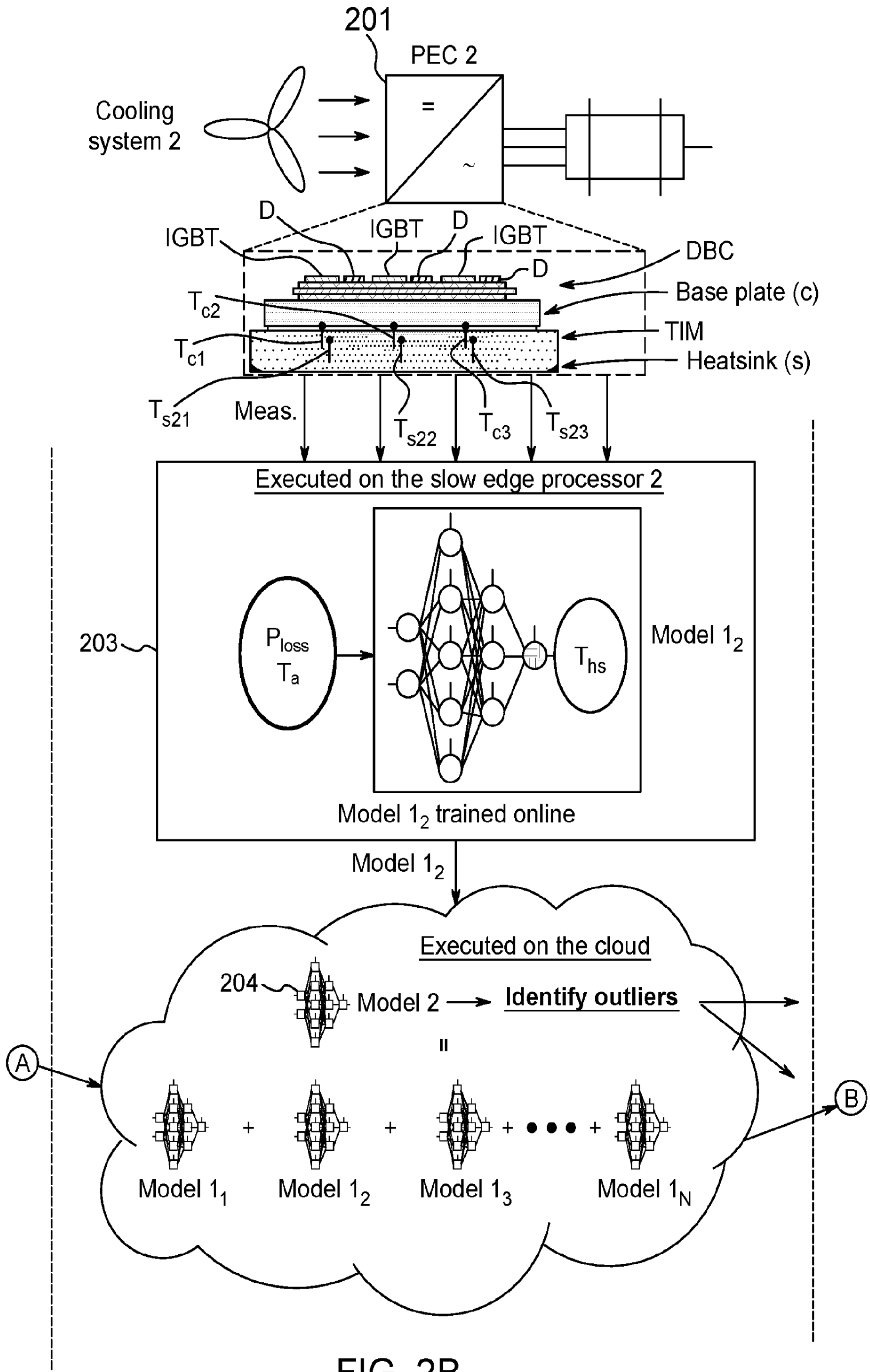

201
PEC 2
Cooling system 2
=
~
IGBT
D
IGBT
D
IGBT
DBC
D
Base plate (c)
T_{c2}
TIM
T_{c1}
Heatsink (s)
T_{s21}
Meas.
T_{s22}
T_{c3}
T_{s23}
Executed on the slow edge processor 2
203
P_{loss}
T_a
T_{hs}
Model 1_2
Model 1_2 trained online
Model 1_2
Executed on the cloud
204
Model 2
Identify outliers
=
A
B
Model 1_1
Model 1_2
Model 1_3
Model 1_N

FIG. 2B

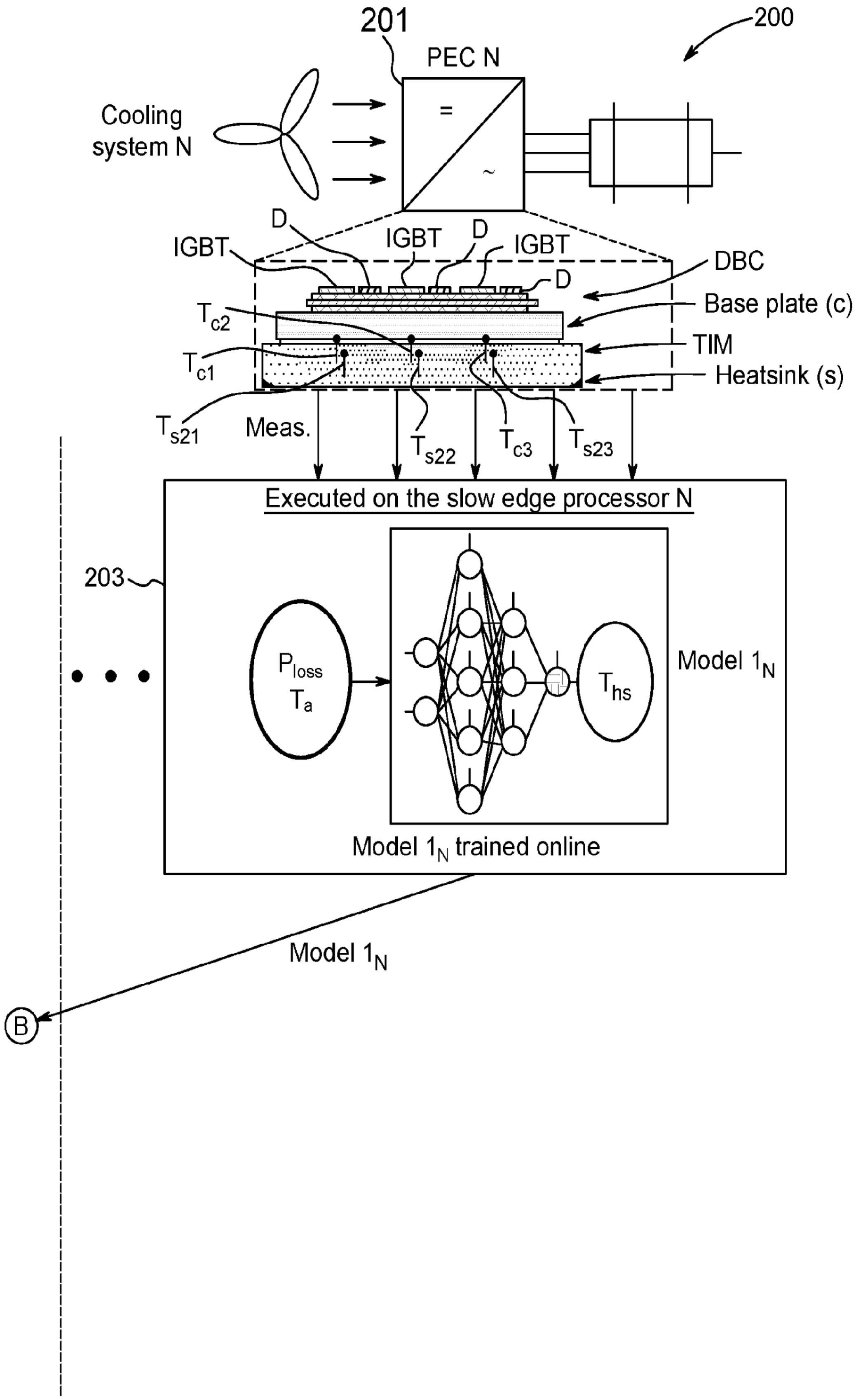

201
200
PEC N
=
~
Cooling
system N
D
IGBT
IGBT
D
IGBT
DBC
D
Base plate (c)
T_{c2}
TIM
T_{c1}
Heatsink (s)
T_{s21}
Meas.
T_{s22}
T_{c3}
T_{s23}
Executed on the slow edge processor N
203
P_{loss}
T_a
T_{hs}
Model 1_N
Model 1_N trained online
Model 1_N
B

FIG. 2C

INTERNATIONAL SEARCH REPORT

International application No
PCT/EP2022/064164

A. CLASSIFICATION OF SUBJECT MATTER
INV. G06N3/04 G06N3/08
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)
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	RAED ABDEL SATER ET AL: "A Federated Learning Approach to Anomaly Detection in Smart Buildings", ARXIV.ORG, CORNELL UNIVERSITY LIBRARY, 201 OLIN LIBRARY CORNELL UNIVERSITY ITHACA, NY 14853, 20 October 2020 (2020-10-20), XP081790939, the whole document -----	1-17
A	KIM SEONGWOO ET AL: "Collaborative Anomaly Detection for Internet of Things based on Federated Learning", 2020 IEEE/CIC INTERNATIONAL CONFERENCE ON COMMUNICATIONS IN CHINA (ICCC), IEEE, 9 August 2020 (2020-08-09), pages 623-628, XP033853306, DOI: 10.1109/ICCC49849.2020.9238913 the whole document -----	1-17

☐ Further documents are listed in the continuation of Box C. ☐ See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance
"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
2 September 2022	20/09/2022

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

1