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(71) **Applicant: DYSON TECHNOLOGY LIMITED** [GB/GB]; Tetbury Hill, Malmesbury Wiltshire SN16 0RP (GB).

(72) **Inventors: JAMMULAMADAKA, Mounica**; c/o Dyson Technology Limited, Tetbury Hill, Malmesbury Wiltshire SN16 0RP (GB). **TERRY-COLLINS, James**; c/o Dyson Technology Limited, Tetbury Hill, Malmesbury Wiltshire SN16 0RP (GB). **WAKEMAN, Matthew**; c/o Dyson Technology Limited, Tetbury Hill, Malmesbury Wiltshire SN16 0RP (GB). **FLETCHER-WILMOT, Lyle**; c/o Dyson Technology Limited, Tetbury Hill, Malmesbury Wiltshire SN16 0RP (GB).

(74) **Agent: DANIEL, Ritchie** et al.; Intellectual Property Department, Dyson Technology Limited, Tetbury Hill, Malmesbury Wiltshire SN16 0RP (GB).

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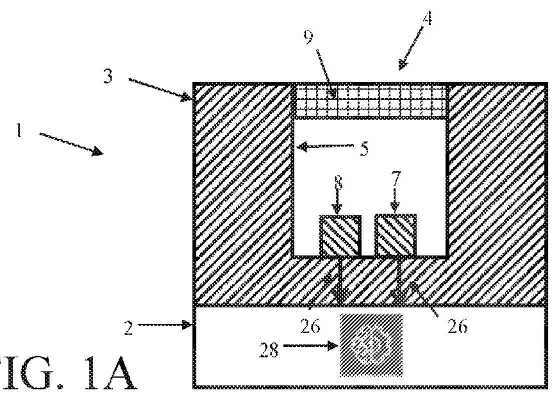

FIG. 1A

(57) **Abstract:** An air quality monitor (1) comprising a plurality of gas monitors (7, 8) for monitoring a plurality of different respective gasses, wherein each gas monitor comprises a respective gas sensor housed within a gas sensing chamber (5) defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere of air, the gas-permeable membrane (9) being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space of the gas sensing chamber for sensing by the respective gas sensors therein; wherein the air quality monitor further comprises an occlusion monitor (28) is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and to output a clearance detection signal accordingly.

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IMPROVEMENTS IN AND RELATING TO AIR QUALITY MONITORING

BACKGROUND

Air quality sensing is a feature of consumer devices, such as wearable devices or smart phones. These devices use air quality sensors that are susceptible to generating false readings when the device is in everyday use as part of an active life e.g., while being worn outdoors in rainy weather or during a sporting activity as part of an active life (e.g., mountain biking, while swimming, while showering) or any other activity which has substances such as dirt or water may interfere with the air quality sensing operation of the device. These substances may easily occlude the sensors used to monitor air quality. While occluded, the sensors may be unable to sample the air.

The present invention has been devised in light of the above considerations.

SUMMARY

At its most general, the invention is the realisation that when the multiple air quality sensors (e.g., gas sensors) of an air quality monitor are occluded (e.g., submerged in water), this condition reveals itself in “patterns” found to exist in the output readings of the air quality sensors (e.g., gas sensors). The inventors have realised that this can be used to identify when air quality readings should be disregarded by a user. The inventors have realised the importance of the continued existence of air quality sensing (e.g., gas sensing) signals from the multiple air quality sensors (e.g., gas sensors) of an air quality monitor when the air quality sensors (e.g., gas sensors) are occluded (e.g., submerged). Patterns in the continued sensing signals can be used to detect the occlusion condition. In air quality sensors (e.g., gas sensors) that are configured inside protected sensing chambers, even during occlusion (e.g., submersion in water), the sensors continue to sense the properties of a gas within the protected sensing chamber, and to output a genuine air quality sensing (e.g., gas sensing) signals accordingly. The inventors have found that the changes in the properties of a gas within the protected sensing chamber are the source of the “patterns” noted above. This is distinct from simply identifying a ‘failure’ of a sensor(s) as might occur if the sensor was directly smothered by water and rendered inoperative.

The absence of an occluding body (e.g., of water) means that the sample of gas within the sensing chamber is an accurate representation of the ambient atmosphere. However, the presence of an occluding body means that the sample of gas within the sensing chamber quickly fails to be an accurate representation of the ambient atmosphere. It is isolated from the ambient atmosphere and is no longer replenished with ‘fresh air’ over time. This means that gasses detected by the sensor become depleted from the isolated air sample within the protected sensing chamber. This means that some of the gases detected by the sensor are depleted and some of the gasses are not dissolved and lodged in the water leading to higher concentration readings. This has been found to be one source of the “patterns” noted above. In addition, the occluding body (e.g., of water) may pollute the isolated sample of air within the protected sensing chamber (e.g., with water vapour, and/or volatiles within the water). This is another source of the “patterns” noted above.

The act of occlusion starts a transition from the state of the sensing chamber being continuously replenished by ambient air to a state of being isolated/depleted and possibly polluted. The act of clearance of an occlusion starts a transition from the state of the sensing chamber being isolated/depleted and possibly polluted to a state of being continuously replenished by ambient air. This transition has also been found to create “patterns” in the output readings of the gas sensors.

It is advantageous to automatically detect when the gas sensors have been occluded. This provides an indication of timeframes when the sensor readings will no-longer be representative of the actual external environment. As the gas exchange is affected by the occlusion of the gas sensors, the sensor readings are also affected. The readings can help understand if/when the device is or is no longer occluded.

In a first aspect, the invention may provide an air quality monitor comprising a plurality of gas monitors for monitoring a plurality of different respective gasses, wherein:

each gas monitor comprises a respective gas sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere of air, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space of the gas sensing chamber for sensing by the respective gas sensors therein;

wherein the air quality monitor further comprises an occlusion monitor configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of (e.g., the creation of, or appearance of) an occlusion of the gas inlet, and to output an occlusion detection signal accordingly.

References herein to a ‘gas monitor’ and a ‘gas sensor’ are intended to include a reference to a monitor (or sensor) for monitoring (or sensing) the presence of, or a concentration of, a given constituent gas within air and/or a reference to a monitor (or sensor) for monitoring (or sensing) the presence of, or a concentration of, particulates within air (i.e., monitoring/sensing a characteristic or quality of the air). A reference herein to ‘particulates’ may include a reference to, but is not limited to, matter in the form of minute separate particles, such as aerosol particles for example.

Desirably, one of the plurality of gas monitors is configured for monitoring water vapour, and the occlusion monitor is configured to detect concurrent changes in outputs of the plurality of gas sensors indicative of an occlusion of the gas inlet by a body of liquid water.

Optionally, the plurality of gas monitors comprises at least three gas monitors for monitoring three different respective gasses.

Preferably, two or more gas sensors of the plurality of gas sensors, or all gas sensors of the plurality of gas sensors, are all housed in one shared gas sensing chamber.

The air quality monitor may comprise:

a temperature monitor comprising a gas temperature sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of a sample of ambient air into the internal space of the gas sensing chamber for sensing by the gas temperature sensor therein;

wherein the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the presence of an occlusion of the gas inlet and to output said occlusion detection signal accordingly.

Desirably, the plurality of gas sensors and the gas temperature sensor are all housed in one shared gas sensing chamber. Optionally, the gas temperature sensor may be configured to measure both temperature and relative humidity. For example, the gas temperature sensor may comprise a single sensor unit configured to measure both temperature and relative humidity (e.g., concurrently or separately). In this way, optionally, a relative humidity sensor may be provided.

Optionally, the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and to output a clearance detection signal accordingly.

Preferably, one of the plurality of gas sensors is configured to sense water vapour, and the occlusion monitor is configured to detect concurrent changes in outputs of the plurality of gas sensors indicative of the clearance of an occlusion by a body of liquid water.

Desirably, the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the clearance of an occlusion of the gas inlet, and to output said clearance detection signal, accordingly.

Optionally, the occlusion monitor is arranged to output said clearance detection signal only once between successive outputs of said occlusion detection signal thereby.

Preferably, the occlusion monitor is arranged to apply a Machine Learning algorithm to detect learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet, and to output said occlusion detection signal when learnt features are detected.

Desirably, the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors.

The learnt features may be detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

The occlusion monitor may be arranged to apply a Machine Learning algorithm to detect further learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of indicative of the clearance of an occlusion of the gas inlet, and to output said clearance detection signal when further learnt features are detected.

Preferably, the further learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors and based on a presence or absence of a previous occlusion detection signal and/or based on a presence or absence of a previous clearance detection signal.

The further learnt features may be detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

In a second aspect, the invention may provide a wearable device comprising an air quality monitor according to the invention in its first aspect.

In a third aspect, the invention may provide a method for monitoring air quality comprising:

providing a plurality of gas monitors and therewith monitoring a plurality of different respective gasses, wherein each gas monitor comprises a respective gas sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere of air, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space of the gas sensing chamber for sensing by the respective gas sensors therein;

detecting concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of (e.g., the creation of, or appearance of) an occlusion of the gas inlet and outputting an occlusion detection signal accordingly.

The method may comprise monitoring water vapour by one of the plurality of gas monitors, and detecting concurrent changes in outputs of the plurality of gas sensors indicative of an occlusion of the gas inlet by a body of liquid water.

The method may comprise monitoring at least three different respective gasses by at least three respective gas monitors of the plurality of gas monitors.

The method may comprise providing two or more gas sensors of the plurality of gas sensors, or all gas sensors of the plurality of gas sensors, in one shared gas sensing chamber.

The method may comprise:

providing a temperature monitor and therewith monitoring a gas temperature, wherein the temperature monitor comprising a gas temperature sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of a sample of ambient air into the internal space of the gas sensing chamber for sensing by the gas temperature sensor therein;

detecting concurrent changes in gas sensor outputs from the plurality of plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the presence of an occlusion of the gas inlet and outputting said occlusion detection signal accordingly.

The method may comprise providing the plurality of gas sensors and the gas temperature sensor in one shared gas sensing chamber.

The method may comprise detecting concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and outputting a clearance detection signal accordingly.

The method may comprise sensing water vapour by one of the plurality of gas monitors, and detecting concurrent changes in outputs of the plurality of gas sensors indicative of the clearance of an occlusion by a body of liquid water.

The method may comprise detecting concurrent changes in gas sensor outputs from the plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the clearance of an occlusion of the gas inlet, and outputting said clearance detection signal accordingly.

The method may comprise outputting said clearance detection signal only once between successive outputs of said occlusion detection signal.

The method may comprise applying a Machine Learning algorithm to detect learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet, and outputting said occlusion detection signal when learnt features are detected.

Preferably, the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors.

Desirably, the learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

The method may comprise applying a Machine Learning algorithm to detect further learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of indicative of the clearance of an occlusion of the gas inlet, and outputting said clearance detection signal when further learnt features are detected.

Desirably, the further learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors and based on a presence or absence of a previous occlusion detection signal and/or based on a presence or absence of a previous clearance detection signal.

Preferably, the further learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

In a fourth aspect, the invention may provide an air quality monitor comprising a plurality of gas monitors for monitoring a plurality of different
respective gasses, wherein:

each gas monitor comprises a respective gas sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere of air, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space of the gas sensing chamber for sensing by the respective gas sensors therein;

wherein the air quality monitor further comprises an occlusion monitor configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of (e.g., the removal of, or disappearance of) an occlusion of the gas inlet, and to output a clearance detection signal accordingly.

References herein to a ‘gas monitor’ and a ‘gas sensor’ are intended to include a reference to a monitor (or sensor) for monitoring (or sensing) the presence of, or a concentration of, a given constituent gas within air and/or a reference to a monitor (or sensor) for monitoring (or sensing) the presence of, or a concentration of, particulates within air (i.e., monitoring/sensing a characteristic or quality of the air). A reference herein to ‘particulates’ may include a reference to, but is not limited to, matter in the form of minute separate particles, such as aerosol particles for example.

Preferably, one of the plurality of gas monitors is configured for monitoring water vapour, and the occlusion monitor is configured to detect concurrent changes in outputs of the plurality of gas sensors indicative of the clearance of an occlusion of the gas inlet by a body of liquid water.

Desirably, the plurality of gas monitors comprises at least three gas monitors for monitoring three different respective gasses.

Two or more gas sensors of the plurality of gas sensors, or all gas sensors of the plurality of gas sensors, may all be housed in one shared gas sensing chamber. Optionally, the gas temperature sensor may be configured to measure both temperature and relative humidity. For example, the gas temperature sensor may comprise a single sensor unit configured to measure both temperature and relative humidity (e.g., concurrently or separately). In this way, optionally, a relative humidity sensor may be provided.

Preferably, the air quality monitor may comprise:

a temperature monitor comprising a gas temperature sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of a sample of ambient air into the internal space of the gas sensing chamber for sensing by the gas temperature sensor therein;

wherein the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the clearance of an occlusion of the gas inlet and to output said clearance detection signal accordingly.

Desirably, the plurality of gas sensors and the gas temperature sensor may be all housed in one shared gas sensing chamber.

Preferably, the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet, and to output an occlusion detection signal accordingly.

Desirably, one of the plurality of gas sensors is configured to sense water vapour, and the occlusion monitor is configured to detect concurrent changes in outputs of the plurality of gas sensors indicative of the presence of an occlusion by a body of liquid water, and to output an occlusion detection signal accordingly.

Preferably, the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the presence of an occlusion of the gas inlet, and to output said occlusion detection signal, accordingly.

Desirably, the occlusion monitor is arranged to output said clearance detection signal only once between successive outputs of said occlusion detection signal thereby.

Preferably, the occlusion monitor is arranged to apply a Machine Learning algorithm to detect learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and to output said clearance detection signal when learnt features are detected.

Desirably, the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors.

Preferably, the learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

Desirably, the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors and based on a presence or absence of a previous occlusion detection signal and/or based on a presence or absence of a previous clearance detection signal.

Preferably, the learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

Desirably, the occlusion monitor is arranged to apply a Machine Learning algorithm to detect further learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet, and to output said occlusion detection signal when further learnt features are detected.

In a fifth aspect, the invention may provide a wearable device comprising an air quality monitor according to the invention in its fourth aspect.

In a sixth aspect, the invention may provide a method for monitoring air quality comprising:

providing a plurality of gas monitors and therewith monitoring a plurality of different respective gasses, wherein each gas monitor comprises a respective gas sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere of air, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space of the gas sensing chamber for sensing by the respective gas sensors therein;

detecting concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of (e.g., the removal of, or disappearance of) an occlusion of the gas inlet, and to output a clearance detection signal accordingly.

The method may comprise monitoring water vapour by one of the plurality of gas monitors, and detecting concurrent changes in outputs of the plurality of gas sensors indicative of the clearance of an occlusion of the gas inlet by a body of liquid water.

The method may comprise monitoring at least three different respective gasses by at least three respective gas monitors of the plurality of gas monitors.

The method may comprise providing two or more gas sensors of the plurality of gas sensors, or all gas sensors of the plurality of gas sensors, in one shared gas sensing chamber.

The method may comprise:

providing a temperature monitor and therewith monitoring a gas temperature, wherein the temperature monitor comprising a gas temperature sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of a sample of ambient air into the internal space of the gas sensing chamber for sensing by the gas temperature sensor therein;

detecting concurrent changes in gas sensor outputs from the plurality of plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the clearance of an occlusion of the gas inlet, and to output a clearance detection signal accordingly.

The method may comprise providing the plurality of gas sensors and the gas temperature sensor in one shared gas sensing chamber.

The method may comprise detecting concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet and outputting an occlusion detection signal accordingly.

The method may comprise sensing water vapour by one of the plurality of gas monitors, and detecting concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet by a body of water, and outputting an occlusion detection signal accordingly.

The method may comprise detecting concurrent changes in gas sensor outputs from the plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the presence of an occlusion of the gas inlet, and outputting said occlusion detection signal accordingly.

The method may comprise outputting said clearance detection signal only once between successive outputs of said occlusion detection signal.

The method may comprise applying a Machine Learning algorithm to detect learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and outputting said clearance detection signal when learnt features are detected.

Preferably, the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors.

Desirably, the learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

Preferably, the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors and based on a presence or absence of a previous occlusion detection signal and/or based on a presence or absence of a previous clearance detection signal.

Desirably, the learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

The method may comprise applying a Machine Learning algorithm to detect further learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet, and outputting said occlusion detection signal when further learnt features are detected.

The invention includes the combination of the aspects and preferred features described except where such a combination is clearly impermissible or expressly avoided.

In any aspect of the invention, disclosed herein, the air-porous water-resistant membrane may comprise, but is not limited to, a comprising an ePTFE (expanded polytetrafluoroethylene) membrane material. The material is preferably with oleophobic. The air-porous water-resistant membrane may comprise a PET (Polyethylene terephthalate) support material. Preferably, the air-porous water-resistant membrane material is configured (e.g., rated) to prevent water ingress in up to 50m water depth (5atm / 505kPa water pressure) for an immersion duration of at least 10 minutes. This characteristic may be determined according to the ISO Rating (ISO 22810). Preferably, the thickness of the air-porous water-resistant membrane material is between about 0.1mm and about 0.5mm, such as about 0.3mm. Preferably, the air-porous water-resistant membrane material is configured (e.g., rated) to permit an airflow through the membrane of between about 500 ml/min/cm2 and about 200 ml/min/cm2, such as about 380 ml/min/cm2. Preferably, the air-porous water-resistant membrane material is porous. Preferably the pore size (or range of pore sizes) of the membrane is such that particulate material is transmissible through the membrane. Preferably, the largest transmissible diameter less than 0.2μm. Preferably, the air-porous water-resistant membrane material is a non-woven material.

BRIEF DESCRIPTION OF THE DRAWINGS

Figures 1A and 1B schematically illustrate an air quality monitor.

Figure 2 schematically illustrates a wearable device comprising an air quality monitor.

Figure 3A and 3B show graphs of gas sensor data from an air quality monitor.

Figure 4 shows a correlation matrix for gas sensor data from an air quality monitor.

Figure 5 show a graph of a distribution of gas sensor data values from an air quality monitor.

Figure 6 shows a graph of gas sensor data from an air quality monitor.

Figure 7 shows a graph of gas sensor data from an air quality monitor.

Figure 8A and 8B show graphs of gas sensor data from an air quality monitor.

Figure 9A and 9B show graphs of gas sensor data from an air quality monitor.

Figure 10A and 10B show graphs of gas sensor data from an air quality monitor.

Figures 11A, 11B and 11C show graphs of gas sensor data from an air quality monitor.

Figures 12A, 12B and 12C show graphs of gas sensor data from an air quality monitor.

Figure 13A and 13B show graphs of gas sensor data from an air quality monitor.

Figure 14A and 14B show graphs of gas sensor data from an air quality monitor.

Figure 15A and 15B show graphs of gas sensor data from an air quality monitor.

Figure 16A and 16B show graphs of gas sensor data from an air quality monitor.

Figure 17A and 17B show graphs of gas sensor data from an air quality monitor.

Figure 18A and 18B show graphs of gas sensor data from an air quality monitor.

Figure 19 shows a neural network in an air quality monitor.

Figure 20 shows a neural network in an air quality monitor.

DETAILED DESCRIPTION

Aspects and embodiments of the present invention will now be discussed with reference to the accompanying figures. Further aspects and embodiments will be apparent to those skilled in the art. All documents mentioned in this text are incorporated herein by reference.

Figures 1A and 1B schematically show an air quality monitor 1 comprising a plurality of gas monitors (7, 8, 2) for monitoring a plurality of different respective gasses. Each gas monitor comprises a respective gas sensor (7, 8) housed within a gas sensing chamber 3 defining an enclosure 5 comprising an internal space and a gas inlet 4 spanned by a gas-permeable membrane 9 that partitions the internal space from an external ambient atmosphere of air. The gas-permeable membrane 9 is permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space (i.e., within enclosure 5) of the gas sensing chamber 3 for sensing by the respective gas sensors (7, 8) therein.

Each of the gas sensors (7, 8) is arranged to generate a sensor output signal 26 indicative of a respective specified property of a gas. The sensor output signal may be continuous or intermittent/periodic (e.g., a succession of discrete sampling times/events), and is preferably continual. The respective sensor output signal 26 is input to a monitoring unit 2 of the gas monitors which is arranged to receive the respective sensor output signal and to generate from it a respective monitoring value that is representative of the respective specified property of a gas being monitored. In this way, the combination of the plurality of gas sensors and the monitoring unit 2 provides a corresponding plurality of gas monitors. It is to be noted that the gas sensing chamber 3 may contain additional gas sensors (not shown). Each gas sensor may be individually configured to detect any one of the following properties of a gas: humidity; relative humidity, carbon dioxide amount or concentration; nitrogen dioxide amount or concentration; carbon dioxide temperature; temperature; Total Volatile Organic Compounds (TVOC) concentration. Of course, it is to be understood that other gasses or properties of a gas may be detected, monitored or sensed for the purposes of the invention disclosed herein, and that the above list is not intended to be exclusive. Readings obtained from direct sensor outputs may be used for (i.e., input to) a Machine Learning (ML) algorithm. The raw readings obtained from the sensors may thereby be considered/used for detection by applying direct sensor output(s) as input to an appropriate ML algorithm.

Volatile organic compounds (VOCs) are a group of compounds with high vapour pressure and low water solubility. These substances do not easily bind to themselves (volatile) or dissolve in water (organic). VOCs are emitted as gasses from everyday products such as building materials and consumer products. Many VOCs are harmful to human health, especially over the long term. The World Health Organization (WHO) definition of TVOC differentiates the volatility (or boiling point) of organic compounds to define Very Volatile Organic Compounds (VVOCs), Volatile Organic Compounds (VOC) and Semi-volatile Organic Compounds (SVOCs). This usually involves the molecular length of the carbon structure; i.e., the number of carbon atoms in the chemical formula. The summation of all VOCs is called the Total Volatile Organic Compounds (TVOC). The volume of gas per classification and the sum of all gases (TVOC) are indicative of the relevant organic compounds found in air.

The air quality monitor 1 may comprise an occlusion monitor 28 configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors (7, 8) indicative of the presence of (i.e., the creation of) an occlusion 11 of the gas inlet 4, and to output an occlusion detection signal 32 (Fig. 1B) accordingly. The occlusion monitor 28 may comprise a data processing unit configured to process the respective monitoring values, each being representative of the respective specified property of a gas being monitored, to identify an indication, within that data, that an occlusion is present at the gas inlet 4. For example, the occlusion may be a barrier of water 11 formed upon the outer surface of the gas-permeable membrane 9 which extends over the gas-permeable membrane to partially or wholly cover the gas inlet 4. The inventors have found that a consequential result of an occlusion, such as a covering of water (either as an isolated film of water or by submersion into a body of water), is that characteristic changes occur in gas sensor outputs from the plurality of gas monitors (7, 8) indicative of the presence of the occlusion of the gas inlet 4. The data processing unit may be configured to process the respective monitoring values to identify such characteristic changes within that data, as is discussed in more detail below. The data processing unit may comprise a processor configured to implement a Machine Learning algorithm trained or configured to identify such characteristic changes within the data.

The air quality monitor 1 may comprise an occlusion monitor 28 configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors (7, 8) indicative of the clearance of an occlusion 11 of the gas inlet, and to output a clearance detection signal 33 (Fig. 1B) accordingly. The occlusion monitor 28 may comprise a data processing unit configured to process the respective monitoring values, each being representative of the respective specified property of a gas being monitored, to identify an indication, within that data, that an occlusion is no longer present at the gas inlet 4. For example, the occlusion may be a barrier of water 11 formed upon the outer surface of the gas-permeable membrane 9 which extends over the gas-permeable membrane to partially or wholly cover the gas inlet 4. The inventors have found that a consequential result of the removal of an occlusion, such as the removal of a covering of water (either as an isolated film of water or by submersion into a body of water), is that characteristic changes occur in gas sensor outputs from the plurality of gas monitors (7, 8) indicating that the occlusion of the gas inlet 4 is no longer present. The data processing unit may be configured to process the respective monitoring values to identify such characteristic changes within that data, as is discussed in more detail below. The data processing unit may comprise a processor configured to implement a Machine Learning algorithm trained or configured to identify such characteristic changes within the data.

It is to be understood that the occlusion monitor 28 may be configured to detect the presence of an occlusion 11 of the gas inlet 4, or in the alternative may be configured to detect the clearance of an occlusion of the gas inlet, or more preferably may be configured to detect both the presence of an occlusion of the gas inlet and the clearance (e.g., subsequently) of an occlusion of the gas inlet. In the following examples, the invention will be discussed in terms of one or more embodiments in which the occlusion monitor 28 is configured to detect both the presence of an occlusion of the gas inlet and the clearance (e.g., subsequently) of an occlusion of the gas inlet. It is to be understood that the following disclosures are equally applicable, mutatis mutandis, to a description of embodiments of the invention in which the occlusion monitor is configured to detect the presence of an occlusion without being configured to detect the clearance of an occlusion, and of embodiments of the invention in which the occlusion monitor is configured to detect the clearance of an occlusion without being configured to detect the presence of (i.e., the creation of) an occlusion.

Examples of a suitable air-porous water-resistant membrane material include, but are not limited to, ePTFE (expanded polytetrafluoroethylene) membrane material, preferably with oleophobic characteristics. The ePTFE membrane may be provided on a PET (Polyethylene terephthalate) support material. Preferably, the air-porous water-resistant membrane material is configured (e.g., rated) to prevent water ingress in up to 50m water depth (5atm / 505kPa water pressure) for an immersion duration of at least 10 minutes. This characteristic may be determined according to the ISO Rating (ISO 22810). Preferably, the thickness of the air-porous water-resistant membrane material is between about 0.1mm and about 0.5mm, such as about 0.3mm. Preferably, the air-porous water-resistant membrane material is configured (e.g., rated) to permit an airflow through the membrane of between about 500 ml/min/cm2 and about 200 ml/min/cm2, such as about 380 ml/min/cm2. Preferably, the air-porous water-resistant membrane material is porous. Preferably the pore size (or range of pore sizes) of the membrane is such that particulate material is transmissible through the membrane. Preferably, the largest transmissible diameter less than 0.2μm. Preferably, the air-porous water-resistant membrane material is a non-woven material.

Examples of suitable air-porous water-resistant membrane materials readily available to the skilled person include, but are not limited to, the following:

An acoustic vent material (e.g., Series GAW344) such as produced by W. L. Gore & Associates, Inc. and described at: https://www.gore.com/system/files/2022-06/gore_acoustic_vent_datasheet_en_jun22_web.pdf

An acoustic vent material such as produced by Kunshan Aynuo New Material Technology Co., Ltd., and described at: http://www.aynuo.com.cn/product/137.html

An acoustic vent material such as produced by Changzhou Creherit Technology CO., Ltd, and described at: http://www.creherit.com/products/p2

An acoustic vent material such as produced by Hangzhou IPRO Membrane Technology Co., Ltd, and described at: https://www.ipromembrane.com/portable-electronics-vents/smart-wearable-device/

Figure 2 schematically illustrates an example of the application of the air quality monitor in a wearable device, such as a smart watch 20. The air quality monitor of the wearable device comprises a first gas sensing chamber 22 and a second gas sensing chamber 24. Each one of these two gas sensing chambers is as described above with reference to Figure 1A and Figure 1B. In this sense, the first gas sensing chamber 22 is part of a first implementation of the air quality monitor 1 of Fig. 1A, and the second gas sensing chamber 24 is part of a second implementation of the air quality monitor 1 of Fig. 1A.

The first gas sensing chamber 22 contains three separate gas sensors each configured to detect a respective different one of the following five gas properties: relative humidity (RH), carbon dioxide amount or concentration (CO_2); nitrogen dioxide amount or concentration (NO_2); Temperature; Total Volatile Organic Compounds (TVOC) concentration. The second gas sensing chamber 24 contains two separate gas sensors each configured to detect a respective different one of the following gas properties that is not sensed by a gas sensor of the first gas sensing chamber 22: relative humidity (RH), carbon dioxide amount or concentration (CO2); nitrogen dioxide amount or concentration (NO2); Temperature; Total Volatile Organic Compounds (TVOC) concentration. In this way the two gas sensing chambers (22, 24) collectively contain five separate gas sensors each configured to detect a respective different one of the above five gas properties. In an alternative example, the first gas sensing chamber 22 may contain the following gas sensors: RH, temperature, NO2 & TVOC, and the second gas sensing chamber 24 contains the CO2 sensor.

The respective sensor output signals 26 of all five gas sensors are input to a common single monitoring unit 2 which is housed within the wearable device 20. Together with the five gas sensors, the monitoring unit 2 defines the gas monitor within the wearable device 20. In Figure 2, the output signals 26 of all five gas sensors, as well as the monitoring unit 2, are also schematically shown in an ‘exploded view’ as removed from the inside of the wearable device 20, for better clarity. It is to be understood that the output signals 26 of the five gas sensors, and the monitoring unit 2, are not external to the wearable device in this example. However, in other examples, the monitoring unit 2 may be implement externally from the wearable device. This may comprise, for example, locating the monitoring unit 2 (e.g., the computational functions) in a separate device with data processing and communications functionality, such as a smartphone, arranged for communication (i.e., for communications and data transmission) with the wearable device. In this example, the wearable device would include a data transmitter/receiver unit (not shown) arranged for communicating with the monitoring unit 2. The monitoring unit 2 may be located on a server (e.g., the cloud) as opposed to on a companion smartphone. The monitoring unit 2 is arranged to receive the five sensor output signals and to generate from them a respective monitoring value that is representative of the respective specified property of a gas being monitored.

The air quality monitor of the wearable device 20 comprises an occlusion monitor 28 configured to detect concurrent changes in gas sensor outputs from the five of gas monitors indicative of the presence of (i.e., the creation of) an occlusion of the gas inlet of either one or both of the first and second gas sensing chambers (22, 24), and to output an occlusion detection signal 32 accordingly. In addition, the occlusion monitor 28 is also configured to detect concurrent changes in gas sensor outputs from the five gas monitors indicative of the clearance of an occlusion of the gas inlet of either one or both of the first and second gas sensing chambers (22, 24), and to output a clearance detection signal 33 accordingly.

The occlusion detection signal 32 and the clearance detection signal 33 are each transmitted to a display unit (not shown) of the wearable device comprising a display screen (i.e., the screen of a smart watch), which is responsive to the received detection signal to generate an output display notification for consumption by the wearer of the device. The output display notification may either inform the user either that an occlusion has been detected and that air quality measurements from the air quality monitor are temporarily ceased (or that they are not ceased but are to be ignored), or inform the user either that an occlusion has been cleared and that air quality measurements from the air quality monitor are resumed (or that they need no longer be ignored).

The occlusion monitor 28 comprises a data processing unit configured to process the respective five monitoring values, to identify an indication, within that data, that an occlusion is present at the gas inlet of either one or both of the two gas sensing chambers (22, 24). The data processing unit preferably comprises a processor configured to implement a Machine Learning algorithm trained to identify such characteristic changes within the data.

The wearable device is therefore able to perform detection of an occlusion (e.g., caused by a submersion of the smart watch under water). The smart watch is equipped with air quality sensors namely NO2, CO2, TVOC concentration, RH and temperature placed inside a respective gas sensing chamber, such as a metal casing, attached to the watch. When an occlusion (e.g., a submersion event) takes place, a water meniscus may form over the gas inlet of one or each of the gas sensing chambers which causes the sensors therein to perform erratically and sudden changes in the sensor readings are observed. This change in sensor readings has been found to be useful in for detecting occlusion (e.g., submersion) event. The pattern of change in sensor readings contains structures that the inventors have discovered are sufficiently reliable to allow them to be learned using a Machine Learning (ML) algorithm (e.g., a Neural Network) that is trained with prior data (e.g., experimental data). The training data is labelled as “occlusion” (e.g., submerged) / “no occlusion” (e.g., not submerged) and this “ground truth” is fed to the ML algorithm to predict events. The prediction (32, 33) is then fed back to the watch as either the occlusion detection signal 32 and the clearance detection signal 33 to alert user that an occlusion (e.g., submersion) event has taken place and the air quality sensor readings may not be reliable and trusted during the event, or that the occlusion has cleared and that the air quality sensor readings may now be considered reliable.

The occlusion (e.g., submersion) detection or clearance detection is considered as a classification problem and any one of several machine learning algorithms may be implemented. The relation between the air quality sensor readings and the occlusion/clearance event is often rather non-linear, and so the implementation of an ML algorithm for submersion detection or clearance detection has been found to be particularly effective. Various feature engineering techniques may be performed on the air quality sensor readings before inputting these to the ML algorithm. Examples include (but are not limited to): normalisation; mean average over a window; standard deviation over a window; low pass filter and high pass filter operations. The ML algorithm may comprise one of the following: Random forest; Decision Tree; Logistic Regression; KNN; shallow neural network algorithms; LSTM (Long short-term memory); GRU (Gated-Recurrent Unit).

Random Forest ML algorithms has been found to generate a high prediction accuracy (e.g., of 96%). However, the number of estimators may be high (e.g., 25 estimators with depth of 9). This algorithm would require larger memory storage and processing time than other ML algirithms.

A classification neural network (e.g., a shallow neural network) may be used for detecting the occlusion events and the clearance events. Figure 19 shows a neural network configured for detecting the occlusion events. Figure 20 shows a neural network configured for detecting the occlusion clearance events corresponding to the resumption of reliable air quality sensing.

The input parameters for this neural network are the sensor readings and their respective rate of change (referred to as "delta" or "gradient" herein) over a predefined time interval (e.g., the previous 30 seconds). These input parameters are preferably normalised before being fed to the neural network. Normalization in machine learning is the process of translating data into e.g., the range [0, 1] (or any other range) or simply transforming data onto the unit sphere (i.e., achieving normalisation). The readings in the present examples were normalised using the equation below:

$$x_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Here, min(x) and max(x) represent the minimum and maximum values defining the lower and upper limits, respectively of the range of values on the data in question. Table 1 shows the various direct sensor readings (RH, CO2, Temp, Temp_CO2) and readings derived from direct sensor outputs (TVOC & NO2), their unit of measurement, and their minimum and maximum values.

Sensor	Minimum	Maximum
RH (%)	25	100
TVOC (ppb)	0	2×10^{12}
NO2 (ppb)	0	200
CO2 (ppm)	-40000	12000
Temp (°C)	10	35
Temp_CO2 (°C)	10	35

Table 1

Table 1 has sensor outputs/readings in different scales. Readings obtained from direct sensor outputs are used for the ML algorithm. The raw readings obtained from the sensors are considered/used for detection by applying direct sensor output(s) as input to an appropriate ML algorithm. When an ML algorithm is trained with these readings, then the algorithm will be more biased towards the sensor which has high range of values. To reduce the bias, all the readings are preferably scaled down (i.e., normalised) to a range [0,1], giving equal priority to all the sensors. The distribution of Relative Humidity (RH) sensor outputs/readings is shown in the Figure 5, to provide an example. The data distribution is not a normal distribution, 60, and so instead of performing "standardization" (i.e., scaling the values such that the mean is 0 and standard deviation as 1) it is preferable to performing "normalization" as noted above (i.e., scaling values between [0,1]).

Neural Networks

An ML algorithm in the form of a neural network has been found to work very well, although other ML algorithms also work well. Details regarding an example of a suitable neural network are discussed below.

To train each neural network, several experiments were conducted with occlusion events (e.g., submersion events) and occlusion clearance events. Approximately 70,000 data points and 75 epochs were used to train, validate, and test each neural network. The neural network shown in Figure 19 is structured for occlusion detection. It comprises a densely connected neural network in which all nodes of successive layers are connected (283, 284, 285). The neural network comprises an input layer 272 comprising twelve input neurons 279, a first hidden layer 274 comprising sixteen neurons 280, a second hidden layer 275 comprising eight neurons 281, and an output layer 276 comprising two neurons 282. The inputs to the input layer are as follows: relative humidity (RH) signals 260; TVOC concentration signals 261 (e.g., readings derived from direct sensor outputs); Temperature signals 262; carbon dioxide Temperature signals 263; carbon dioxide (CO_2) concentration signals 264; nitrogen dioxide (NO_2) concentration signals 265 (e.g., readings derived from direct sensor outputs); the rate of change of relative humidity (RH) signals 266; the rate of change of TVOC concentration signals 271; the rate of change of Temperature signals 269; the rate of change of carbon dioxide Temperature signals 270; the rate of change of carbon dioxide concentration signals 267; the rate of change of nitrogen dioxide concentration signals 268. Each of the input signals (260 – 271) comprised the result of passing the original sensor signal in question through a low-pass filtering (LPF) process to remove high-frequency noise.

The output layer provides two outputs (277, 278) one of which, 277, indicates an occlusion event has taken place (e.g., “submerged”) when it possesses a high value (e.g., output = 1.0) and the other of which, 278, indicates an occlusion event has not taken place (e.g., “unsubmerged”) when it possesses a high value (e.g., output = 1.0). Thus, the output layer determines if the occlusion (e.g., submersion) event occurred or not. The neural network gives about 95% accuracy. The algorithm yielded good accuracy, compact and easy deployment on to the microprocessor of the smart watch 20.

The neural network shown in Figure 20 is structured for occlusion clearance detection. It comprises a densely connected neural network in which all nodes of successive layers are connected (2314, 315, 316). The neural network comprises an input layer 304 comprising twelve input neurons 307, a first hidden layer 317 comprising sixteen neurons 308, a second hidden layer 310 comprising eight neurons 309, and an output layer 306 comprising two neurons 313. The inputs to the input layer are as follows: relative humidity (RH) signals 260; TVOC concentration signals 261; Temperature signals 262; carbon dioxide Temperature signals 263; carbon dioxide (CO2) concentration signals 264; nitrogen dioxide (NO2) concentration signals 265; the rate of change of relative humidity (RH) signals 266; the rate of change of TVOC concentration signals 271; the rate of change of Temperature signals 269; the rate of change of carbon dioxide Temperature signals 270; the rate of change of carbon dioxide concentration signals 267; the rate of change of nitrogen dioxide concentration signals 268; previous non-occluded (reliable) state 302; previous occluded (e.g., submersion) state 303. Each of the input signals (260 – 271) comprised the result of passing the original sensor signal in question through a low-pass filtering (LPF) process to remove high-frequency noise.

A “previous reliable state” (i.e., non-occluded / occluded state) 302 corresponds to a sensor value which has been previously identified as corresponding to a non-occluded / occluded state of the gas sensing chamber containing the gas sensor from which the readings came. Similarly, a “previous submerged state” 303 corresponds to a sensor value which has been previously identified as corresponding to an occluded / non-occluded state of the gas sensing chamber containing the gas sensor from which the readings came. By including these two additional input data items, the inventors have found that the neural network may be more reliably trained or previous occlusion state to distinguish between future occluded and non-occluded states. Preferably, readings from all the sensors are used to detect an occlusion state.

The output layer 306 provides two outputs (311, 312) one of which, 311, indicates an occlusion event has been cleared (e.g., “reliable”) when it possesses a high value (e.g., output = 1.0) and the other of which, 312, indicates an occlusion event has not been cleared (e.g., “unreliable”) when it possesses a high value (e.g., output = 1.0). Thus, the output layer 306 determines if the occlusion (e.g., submersion) event has been cleared or not. The neural network gives about 95% accuracy. The algorithm yielded good accuracy, compact and easy deployment on to the microprocessor of the smart watch 20.

Figures 3A and 3B illustrate examples of a time series of values of a sensor output 26 corresponding to a relative humidity sensor – this being either one of the two gas sensors (7, 8) within the air quality monitor in the wearable device, such as the smart watch 20. The time series of values shown in the graphs of figures 3A and 3B came from a wearable device 20 before, during, and after it was submerged in water. The time interval of submersion is indicated in the figures as the interval between vertical lines 48 and 46. The data points indicated by reference numeral 40 in Figure 3A correspond to the signal output from the relative humidity sensor on the smart watch 20 was not submerged under water. The data points indicated by reference numeral 44 in Figure 3A highlight the signal output from the relative humidity sensor when the smart watch 20 was submerged. These classifications correspond to ground truth classification.

Figure 3B illustrates the same time series of values of the sensor output 26 from the relative humidity sensor as is shown in Figure 3A. However, in Figure 3B, those sensor output values that were classified by the ML algorithm as corresponding to a submersion event, are indicated with reference numerals 50 and 52. In these examples the submersion event is correctly predicted as is seen in data values 50. The classification of a submersion event can sometimes persist briefly after the event, and an example of this is identified by data values 52. However, this is a relatively benign misclassification because it is driven by a genuine submersion event. No false triggers are observed in advance of the submersion event.

One may consider the correlation between the sensor readings (all of which are continuous data) by calculating a Pearson Correlation Coefficient between different sensor outputs. A correlation matrix was calculated accordingly, among the sensor readings and the labelled data, and this is shown in Figure 4. From Figure 4 it can be inferred that for solving the submersion detection problem, all the sensor readings are not much related to the submerged data. Relative Humidity (RH) has been found to have a relatively strong impact and so does temperature sensor readings.

The sensor readings have been found often to not have any linear dependency on each other, making it a complex problem for classifying as reliable or submerged. The pair plots demonstrating the same are provided in Figures 11A, 11B and 11C and in Figures 12A, 12B and 12C as an example illustrating this. The inventors have found that the data nevertheless possesses non-linearities that make it surprisingly amenable to classification by ML algorithms which have been found to be able consider these non-linearities. The ML algorithms are able to provide good classification algorithms. In the pair plots of Figures 11A, 11B and 11C and Figures 12A, 12B and 12C, clusters of data points corresponding to reliability state “0.0” are indicated by a surrounding dashed-line ellipse annotated as “0.0”, for visual aid. Similarly, clusters of data points corresponding to reliability state “1.0” are indicated by a surrounding dashed-line ellipse annotated as “1.0”, for visual aid.

From the correlation matrix of Figure 4 and the pair plots in Figures 11A-C and Figures 12A-C, it is clear that there non-linearities between the features in the air quality sensor data and some features have relatively less influence for classifying an occlusion (submersion) state and a non-occlusion (reliability) state than other features do. An ablation study was performed with a shallow neural network. The ablation study was performed for both occlusion (submersion) detection and non-occlusion (reliability) detection are presented in Table 2 and Table 3 respectively.

RH	TVOC	Temperature	CO2 Temperature	CO2	NO2	Accuracy
✓	✓	✓	✓	✓	✓	94.61
	✓	✓	✓	✓	✓	66.78
✓		✓	✓	✓	✓	91.45
✓	✓			✓	✓	79.93
✓	✓	✓	✓	✓		91.20
✓	✓	✓	✓		✓	92.02
	✓			✓	✓	66.27

Table 2 - occlusion (submersion) detection

RH	TVOC	Temperature	CO2 Temperature	CO2	NO2	Accuracy
✓	✓	✓	✓	✓	✓	99.03
	✓	✓	✓	✓	✓	82.21
✓		✓	✓	✓	✓	98.80
✓	✓			✓	✓	92.35
✓	✓	✓	✓	✓		98.46
✓	✓	✓	✓		✓	98.06
	✓			✓	✓	79.45

Table 3 - non-occlusion (reliability) detection

From the ablation study for both occlusion (submersion) detection and non-occlusion (reliability) detection, it is demonstrated that influence of many (e.g., all) the sensor readings yields better detection. Considering this study, all the sensor readings were used to examine various ML algorithms for both occlusion (submersion) detection and non-occlusion (reliability) detection.

Many ML algorithms have been considered and tested. For comparison prediction accuracy results are compiled in Table 4 which lists occlusion (submersion) detection accuracy (%), and in Table 5 for non-occlusion (reliability) detection accuracy (%).

	Decision Tree	Logistic Regression	K Nearest Neighbours	Neural Network	Random Forest
Averaged over 30 Sec Window	96.34	96.95	12.22	50.61	97.56
Un-Normalised	**96**	95.84	34.75	89.99	99.43
Normalised	95.25	89.47	55.40	82.42	99.66
Normalised with delta Gradient	93.89	85.25	69.74	**94.61**	99.02
Low pass filter with Delta Gradient				**96.44**	

Table 4 - occlusion (submersion) detection accuracy (%)

	Decision Tree	Logistic Regression	K Nearest Neighbours	Neural Network	Random Forest
Averaged over 30 Sec Window	95.4	86	14.8	36.9	99.1
Un-Normalised	**99.5**	98.6	22.2	97.8	99.9
Normalised	86.2	84.1	24.3	95.4	99.7
Normalised with delta Gradient	87.2	84.1	31.8	**98.8**	99.7
Low pass filter with Delta Gradient				**98.52**	

Table 5 - non-occlusion (reliability) detection accuracy (%)

The following ML algorithms were considered, and listed in Table 4 and Table 5: (1) a Decision Tree; (2) Logistic Regression; (3) a 'K-nearest-Neighbours' algorithm; (4) a Neural Network; (5) a Random Forrest. Each of these was considered under four or five of the following conditions: (i) with averaging of sensor data over a 30 second window prior to input to the ML algorithm; (ii) with un-normalised sensor data as input to the ML algorithm; (iii) with normalised sensor data as input to the ML algorithm; (iv) with normalised sensor data as input to the ML algorithm, and the use of "delta" gradient/derivative values of the sensor data as inputs to the ML algorithm; (v) with pre-filtering of sensor data with a low-pass filter (LPF) before being input to the ML algorithm, and the use of "delta" gradient/derivative values of the sensor data as inputs to the ML algorithm.

The following ML algorithms performed well under the specified conditions: (a) a Decision Tree with raw data; (b) a shallow Neural Network with "delta" gradient/derivative inputs and normalised data; (c) a shallow Neural Network in which a low pass filter was pre-applied to input data, with “delta” gradient/derivative inputs; (d) a logistic regression with averaging of data over a 30 sec window.

Occlusion Detection

Figures 6 and 7 show the results of an experiment in which the smart watch 20 was briefly submerged under water. In more detail, figures 6 and 7 contain a time series of values of a sensor output 26 corresponding to a relative humidity sensor – this being either one of the two gas sensors (7, 8) within the air quality monitor in the wearable device, such as the smart watch 20. The time series of values shown in the graphs of figures 6 and 7 came from a wearable device 20 before, during, and after it was submerged in water. The time interval of submersion is indicated in the figures as the interval between vertical lines 84 and 86. The data points indicated by reference numeral 80 in Figure 6 correspond to the signal output from the relative humidity sensor on the smart watch 20 was not submerged under water. The data points indicated by reference numeral 82 in Figure 6 highlight the signal output from the relative humidity sensor when the smart watch 20 was submerged. These classifications correspond to ground truth classification. The interval of time extending between the dashed vertical lines 88 and 80 of figures 6 and 7 correspond to a non-submerged state when the smart watch was taken outdoors into an ambient environment that had a significantly higher humidity than the indoor environment where the smart watch resided for all other time intervals within the graphs of figures 6 and 7.

Figure 7 illustrates the same time series of values of the sensor output 26 from the relative humidity sensor as is shown in Figure 6. However, in Figure 7, those sensor output values that were classified by the Decision Tree ML algorithm (using un-normalised data) as corresponding to a submersion event, are indicated with reference numerals 92. In these examples the submersion event is correctly predicted. The classification of a submersion event can sometimes persist briefly after the event, and an example of this is identified by data values 92. However, this is a relatively benign misclassification because it is driven by a genuine submersion event. However, several false triggers are observed after the submersion event when the smart watch was taken outdoors into an ambient environment that had a significantly higher humidity.

Figure 8A illustrates the same time series of values of the sensor output 26 from the relative humidity sensor as is shown in Figure 6. However, in Figure 8A, those sensor output values that were classified by the Neural Network ML algorithm (using “delta” gradient input values) as corresponding to a submersion event, are indicated with reference numerals 102. In these examples the submersion event is correctly predicted. The classification of a submersion event can sometimes persist briefly after the event, and an example of this is identified by data values 102. However, as noted above, this is a relatively benign misclassification because it is driven by a genuine submersion event. However, only a few false triggers are observed before the submersion event, and none when the smart watch was taken outdoors into an ambient environment that had a significantly higher humidity.

Figure 8B illustrates the same time series of values of the sensor output 26 from the relative humidity sensor as is shown in Figure 6. However, in Figure 8B, those sensor output values that were classified by the Neural Network ML algorithm (using “delta” gradient input values and low-pass filtered (LPF) input data) as corresponding to a submersion event, are indicated with reference numerals 112. In these examples the submersion event is correctly predicted. The classification of a submersion event does not persist after the event, and no false triggers are observed before the submersion event, and none when the smart watch was taken outdoors into an ambient environment that had a significantly higher humidity.

From the graphs it can be inferred that the trained decision tree was generating a lot of false positives. A shallow neural network with inputs comprising both the sensor readings and the delta gradient values, together with previous submerged and reliable states as inputs, was found to perform well and resulted in fewer false positives. Indeed, such a shallow neural network which was fed with low pass filtered sensor readings and delta gradient values performed even better, with better accuracy and precision.

Occlusion Clearance Detection (reliability State)

Figure 9A illustrates the same time series of values of the sensor output 26 from the relative humidity sensor as is shown in Figure 6. However, in Figure 9A, those sensor output values that were reclassified according to whether or not they corresponded to: (a) the absence of an occlusion (pre/post-submersion) and, (b) the sensor was operating in a reliable state. The data points indicated by reference numeral 132 in Figure 9A highlight the signal output from the relative humidity sensor when the smart watch 20 was not submerged and the sensor was once more operating in a reliable state. Data corresponding to the non-reliable state of the sensor, both during and shortly after submersion of the smart watch, are indicated by the reference numeral 800 in Figure 9A. These classifications correspond to ground truth classification.

Figure 9B illustrates classification of this data by the Decision Tree ML algorithm (using un-normalised input values) as corresponding to a clearance of an occlusion (post-submersion) and the sensor operating in a reliable state, and these classifications are indicated with reference numerals 122. In these examples the reliable state is correctly predicted. The classification of a submersion event is identified by data values 801. Only a few false classifications are observed before and after the submersion event.

Figure 10A illustrates the sensor output values that were classified by the Neural Network ML algorithm (using “delta” gradient input values) as corresponding to absence of an occlusion (pre/post-submersion) and the sensor operating in a reliable state. This data is indicated with reference numerals 142. In these examples the absence of an occlusion (pre/post-submersion) and the sensor operating in a reliable state, is correctly predicted. In addition, the state occlusion (submersion) and the sensor operating in an unreliable state is also correctly predicted, as indicated by reference numerals 802.

Figure 10B illustrates the sensor output values that were classified by the Neural Network ML algorithm (using “delta” gradient input values and low-pass filtered (LPF) input data) as corresponding to absence of an occlusion (pre/post-submersion) and the sensor operating in a reliable state. This data is indicated with reference numerals 152. In these examples the absence of an occlusion (pre/post-submersion) and the sensor operating in a reliable state, is correctly predicted. In addition, the state occlusion (submersion) and the sensor operating in an unreliable state is also correctly predicted, as indicated by reference numerals 803. From the graphs it can be inferred that the trained decision tree was generating a lot of false positives. A shallow neural network with low pass filtered sensor readings and delta gradient values as inputs is performing well with few less false positives. However, a shallow neural network which was fed with the sensor readings and delta gradient values and with previous submerged and reliable states, as inputs, is seen to perform even better, with better accuracy and precision.

Figures 13A-13B to 18A-18B show examples of the sensor output values generated by different air quality gas sensors employed in the smart watch 20. These output values/readings were obtained by repeating submersion/non-submersion tests within a controlled test chamber. In Figure 13A, CO2 readings of a submerged wearable device are shown. Conversely, Figure 13B shows CO2 readings of an un-submerged device are shown. In Figure 14A, NO2 readings of a submerged wearable device are shown. The readings shown by line 175 is corresponds to NO2 in the test chamber in which the experiments took place. Figure 14B shows NO2 readings of the un-submerged device. Again, line 184 corresponds to readings of the NO2 in the test chamber. In Figure 15A, RH (relative Humidity) readings of the submerged device are shown, while Figure 15B shows RH (Relative Humidity) readings of the un-submerged device. In Figure 16A, temperature readings of the submerged device are shown, whereas Figure 16B shows readings of temperature from the un-submerged device. Figure 17A shows the readings of sensors configured to sense the temperature of CO2 from the submerged device, and Figure 17B shows such temperature of CO2 readings from the un-submerged device. Finally, Figure 18A shows TVOC concentration readings from the submerged device, and Figure 18B shows TVOC concentration readings of the un-submerged device. The lines 245 and 254 are a reference TVOC reading taken from within the test chamber.

The individual graph lines (data) shown in Figures 13A-13B to 18A-18B (i.e., lines 160 – 164; 170-173; 174-179; 180-184; 190-194; 200-203; 210-214; 220-223; 230-234; 240-243; 244-249; 250-254) correspond to repeated submersion/non-submersion tests within a controlled test chamber. These graphs are useful in permitting a comparison of how the sensor readings are relatively erratic when the occlusion is present. The un-submerged readings are used as frame of reference are far more stable. It signifies the benefits of using ML algorithms to determine the “patterns” noted above, for state detection.

The features disclosed in the foregoing description, or in the following claims, or in the accompanying drawings, expressed in their specific forms or in terms of a means for performing the disclosed function, or a method or process for obtaining the disclosed results, as appropriate, may, separately, or in any combination of such features, be utilised for realising the invention in diverse forms thereof.

While the invention has been described in conjunction with the exemplary embodiments described above, many equivalent modifications and variations will be apparent to those skilled in the art when given this disclosure. Accordingly, the exemplary embodiments of the invention set forth above are considered to be illustrative and not limiting. Various changes to the described embodiments may be made without departing from the spirit and scope of the invention.

For the avoidance of any doubt, any theoretical explanations provided herein are provided for the purposes of improving the understanding of a reader. The inventors do not wish to be bound by any of these theoretical explanations.

Any section headings used herein are for organizational purposes only and are not to be construed as limiting the subject matter described.

Throughout this specification, including the claims which follow, unless the context requires otherwise, the word “comprise” and “include”, and variations such as “comprises”, “comprising”, and “including” will be understood to imply the inclusion of a stated integer or step or group of integers or steps but not the exclusion of any other integer or step or group of integers or steps.

It must be noted that, as used in the specification and the appended claims, the singular forms “a,” “an,” and “the” include plural referents unless the context clearly dictates otherwise. Ranges may be expressed herein as from “about” one particular value, and/or to “about” another particular value. When such a range is expressed, another embodiment includes from the one particular value and/or to the other particular value. Similarly, when values are expressed as approximations, by the use of the antecedent “about,” it will be understood that the particular value forms another embodiment. The term “about” in relation to a numerical value is optional and means for example +/- 10%.

CLAIMS

1. An air quality monitor comprising a plurality of gas monitors for monitoring a plurality of different respective gasses, wherein:

each gas monitor comprises a respective gas sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere of air, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space of the gas sensing chamber for sensing by the respective gas sensors therein;

wherein the air quality monitor further comprises an occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and to output a clearance detection signal accordingly.

2. An air quality monitor according to any preceding claim wherein one of the plurality of gas monitors is configured for monitoring water vapour, and the occlusion monitor is configured to detect concurrent changes in outputs of the plurality of gas sensors indicative of the clearance of an occlusion of the gas inlet by a body of liquid water.

3. An air quality monitor according to any preceding claim wherein the plurality of gas monitors comprises at least three gas monitors for monitoring three different respective gasses.

4. An air quality monitor according to any preceding claim wherein two or more gas sensors of the plurality of gas sensors, or all gas sensors of the plurality of gas sensors, are all housed in one shared gas sensing chamber.

5. An air quality monitor according to any preceding claim comprising:

a temperature monitor comprising a gas temperature sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of a sample of ambient air into the internal space of the gas sensing chamber for sensing by the gas temperature sensor therein;

wherein the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the clearance of an occlusion of the gas inlet and to output said clearance detection signal accordingly.

6. An air quality monitor according to claim 5 wherein the plurality of gas sensors and the gas temperature sensor are all housed in one shared gas sensing chamber.

7. An air quality monitor according to any preceding claim wherein the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet, and to output an occlusion detection signal accordingly.

8. An air quality monitor according to claim 7 wherein one of the plurality of gas sensors is configured to sense water vapour, and the occlusion monitor is configured to detect concurrent changes in outputs of the plurality of gas sensors indicative of the presence of an occlusion by a body of liquid water, and to output an occlusion detection signal accordingly.

9. An air quality monitor according to claim 7 when dependent on claim 5 wherein the occlusion monitor is configured to detect concurrent changes in gas sensor outputs from the plurality of gas monitors and in a gas temperature sensor output from the temperature monitor indicative of the presence of an occlusion of the gas inlet, and to output said occlusion detection signal, accordingly.

10. An air quality monitor according to any of claims 7 to 9 wherein the occlusion monitor is arranged to output said clearance detection signal only once between successive outputs of said occlusion detection signal thereby.

11. An air quality monitor according to any preceding claim wherein the occlusion monitor is arranged to apply a Machine Learning algorithm to detect learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and to output said clearance detection signal when learnt features are detected.

12. An air quality monitor according to claim 11 wherein the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors.

13. An air quality monitor according to claim 12 when dependent on claim 5 wherein the learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

14. An air quality monitor according to any of claims 11 to 13 wherein the learnt features are detected by implementing a Neural Network algorithm based on concurrent values of the gas sensor outputs from the plurality of gas monitors and based on rates of change of the concurrent values of the gas sensor outputs from the plurality of gas monitors and based on a presence or absence of a previous occlusion detection signal and/or based on a presence or absence of a previous clearance detection signal.

15. An air quality monitor according to any of claims 11 to 14 wherein the learnt features are detected by implementing said Neural Network algorithm further based on concurrent values of the gas temperature sensor output from the temperature monitor and

based on rates of change of the concurrent values of the gas temperature sensor output from the temperature monitor.

16. An air quality monitor according to any of claims 7 to 15 wherein the occlusion monitor is arranged to apply a Machine Learning algorithm to detect further learnt features in concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the presence of an occlusion of the gas inlet, and to output said occlusion detection signal when further learnt features are detected.

17. A wearable device comprising an air quality monitor according to any preceding claim.

18. A method for monitoring air quality comprising:

providing a plurality of gas monitors and therewith monitoring a plurality of different respective gasses, wherein each gas monitor comprises a respective gas sensor housed within a gas sensing chamber defining an enclosure comprising an internal space and a gas inlet spanned by a gas-permeable membrane that partitions the internal space from an external ambient atmosphere of air, the gas-permeable membrane being permeable to ambient air and substantially impermeable to liquid water thereby allowing passage of the plurality of different gasses within ambient air into the internal space of the gas sensing chamber for sensing by the respective gas sensors therein;

detecting concurrent changes in gas sensor outputs from the plurality of gas monitors indicative of the clearance of an occlusion of the gas inlet, and to output a clearance detection signal accordingly.

19. A method according to claim 18 including monitoring water vapour by one of the plurality of gas monitors, and detecting concurrent changes in outputs of the plurality of gas sensors indicative of the clearance of an occlusion of the gas inlet by a body of liquid water.

20. A method according to any of claims 18 to 19 including monitoring at least three different respective gasses by at least three respective gas monitors of the plurality of gas monitors.

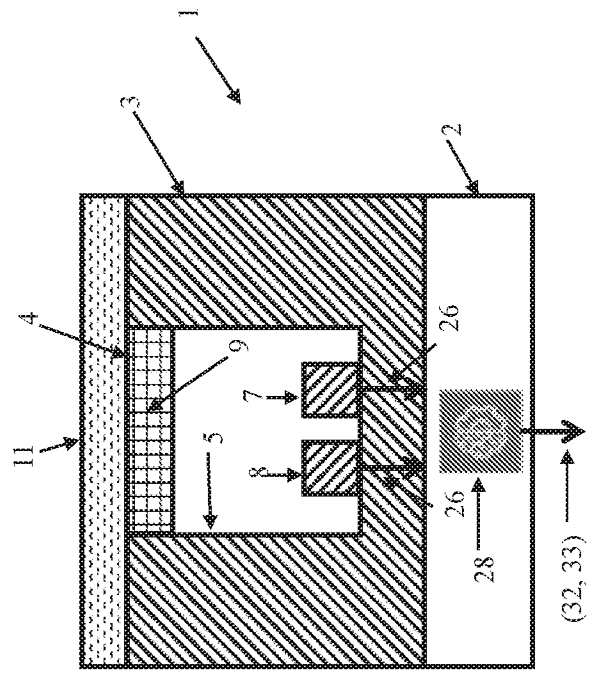

FIG. 1B

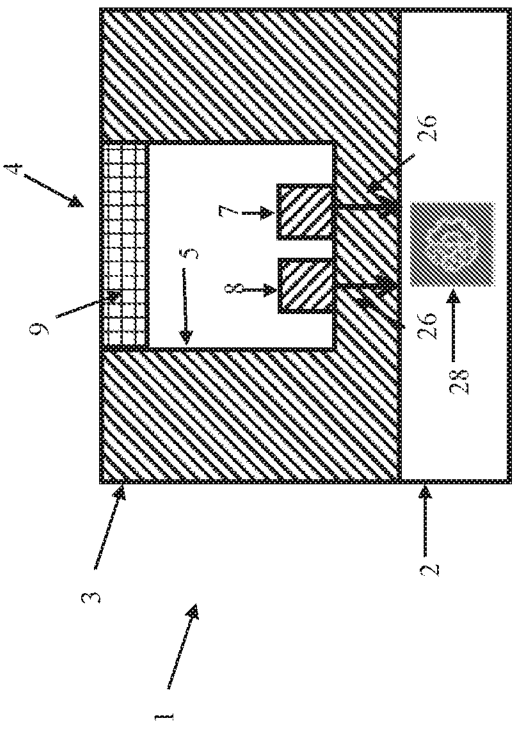

FIG. 1A

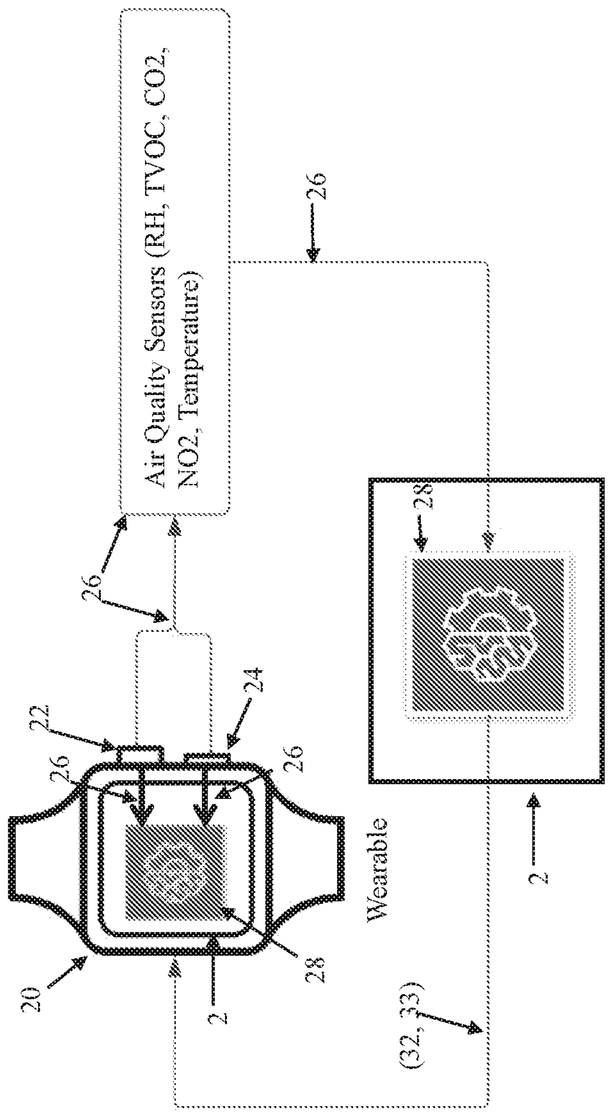
Air Quality Sensors (RH, TVOC, CO2, NO2, Temperature)
26
26
26
26
22
24
20
28
28
2
2
Wearable
(32, 33)

FIG. 2

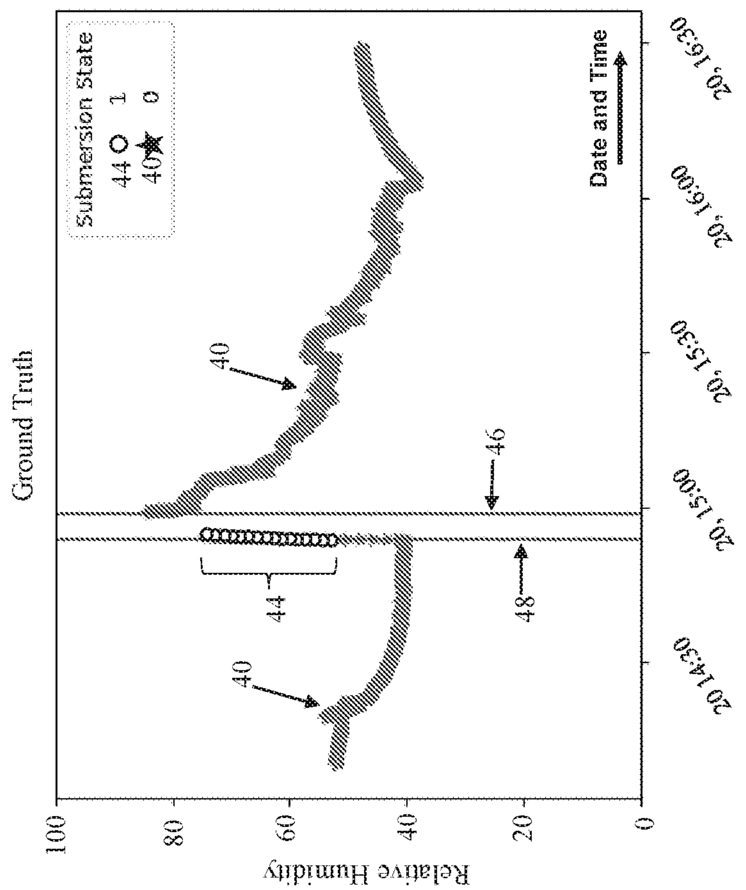
Ground Truth
Submersion State
44 ○ 1
40 ★ 0
Relative Humidity
100
80
60
40
20
0
20,14:30
20,15:00
20,15:30
20,16:00
20,16:30
Date and Time
40
40
44
46
48

FIG. 3A

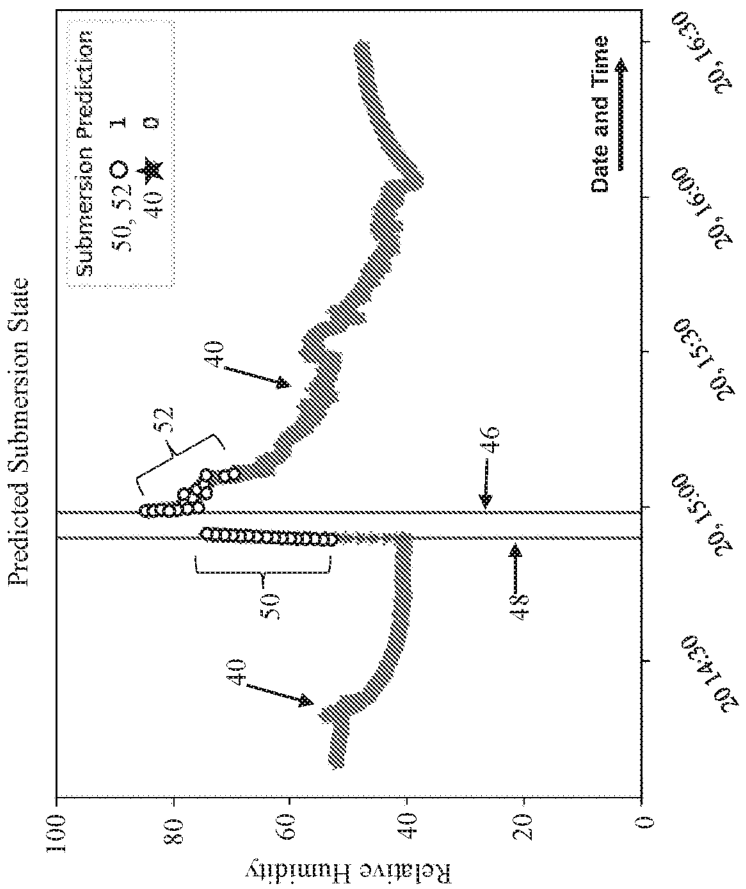
Predicted Submersion State
Submersion Prediction
50, 52 ○ 1
40 ★ 0
Relative Humidity
100
80
60
40
20
0
20,14:30
20,15:00
20,15:30
20,16:00
20,16:30
Date and Time
40
40
50
52
46
48

FIG. 3B

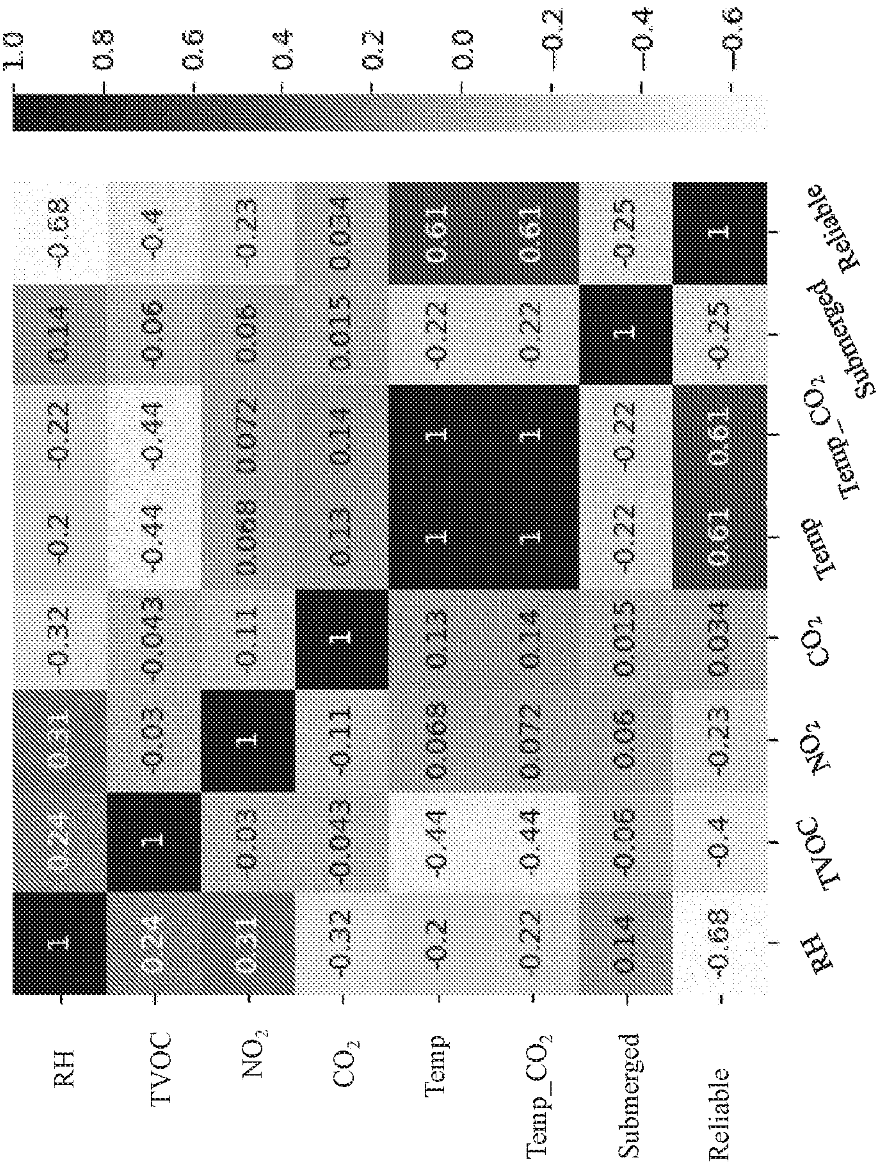
RH
TVOC
NO_2
CO_2
Temp
Temp_CO_2
Submerged
Reliable
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

FIG. 4

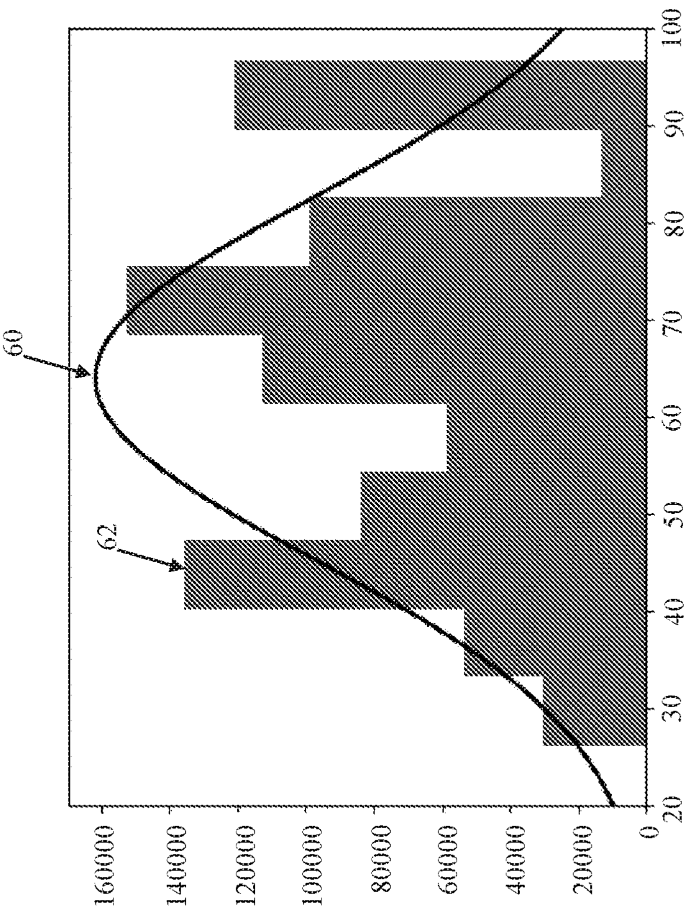
160000
140000
120000
100000
80000
60000
40000
20000
0
20
30
40
50
60
70
80
90
100
60
62

FIG. 5

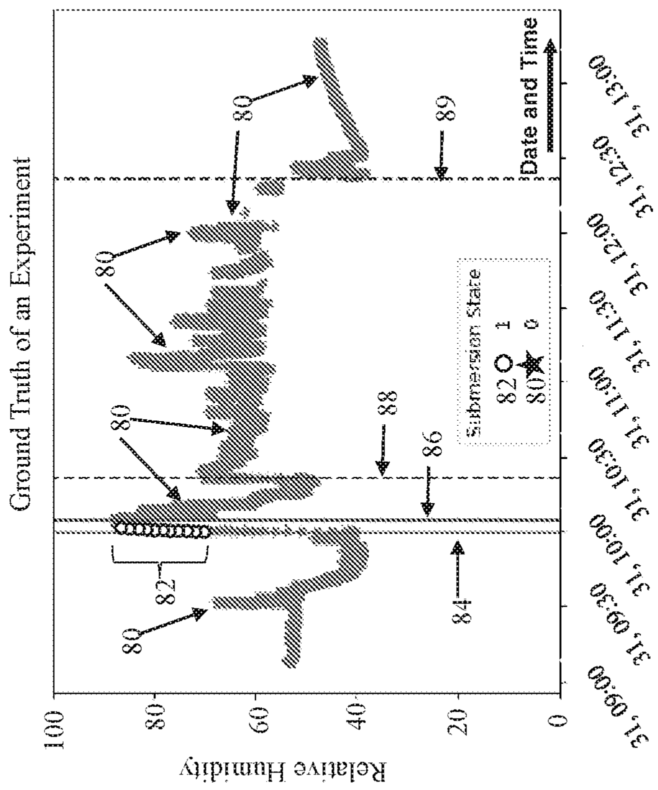
Ground Truth of an Experiment
Relative Humidity
100
80
60
40
20
0
31, 09:00
31, 09:30
31, 10:00
31, 10:30
31, 11:00
31, 11:30
31, 12:00
31, 12:30
31, 13:00
Date and Time
Submersion State
82 1
80 0
80
82
84
86
88
89

FIG. 6

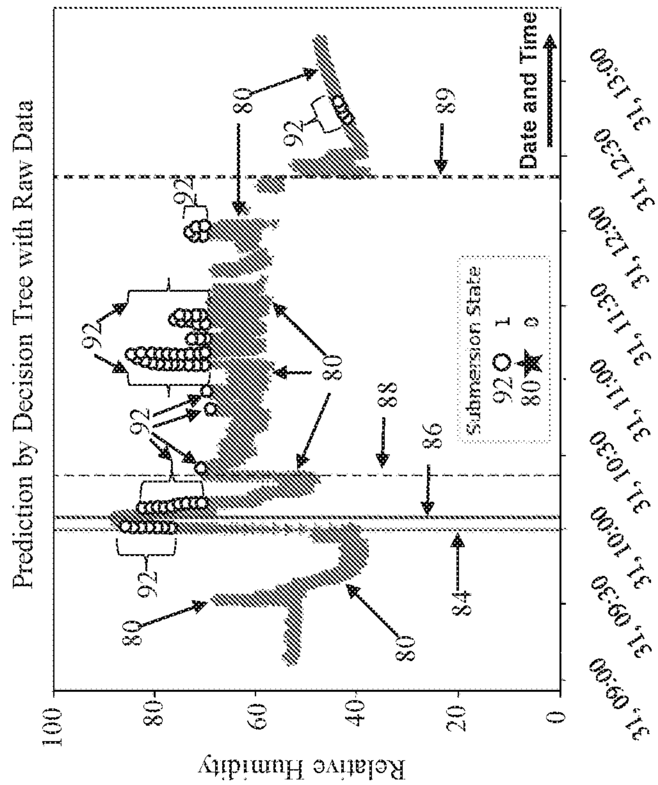
Prediction by Decision Tree with Raw Data
Relative Humidity
100
80
60
40
20
0
31, 09:00
31, 09:30
31, 10:00
31, 10:30
31, 11:00
31, 11:30
31, 12:00
31, 12:30
31, 13:00
Date and Time
Submersion State
92 1
80 0
80
92
84
86
88
89

FIG. 7

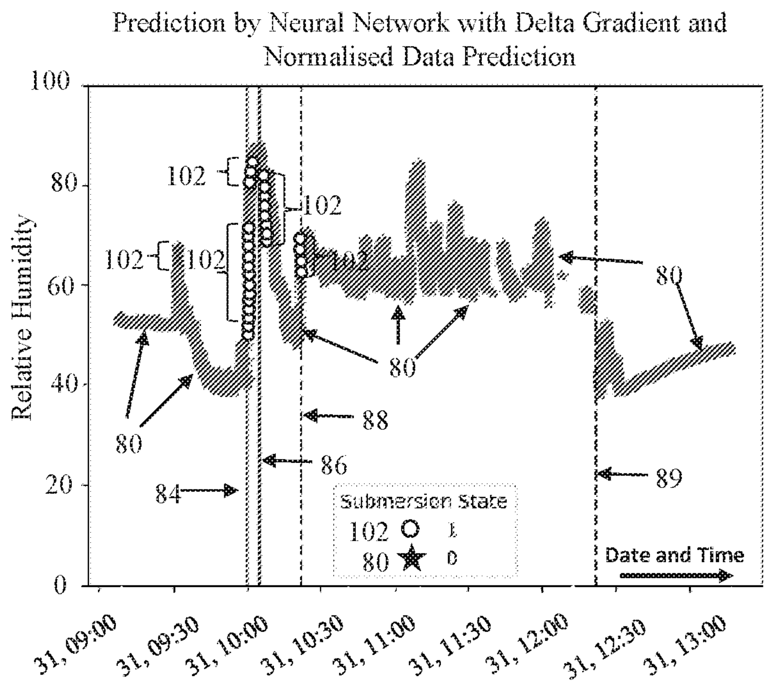
Prediction by Neural Network with Delta Gradient and
Normalised Data Prediction
Relative Humidity
100
80
60
40
20
0
102
102
102
102
102
80
80
80
80
84
86
88
89
Submersion State
102 1
80 0
Date and Time
31, 09:00
31, 09:30
31, 10:00
31, 10:30
31, 11:00
31, 11:30
31, 12:00
31, 12:30
31, 13:00

FIG. 8A

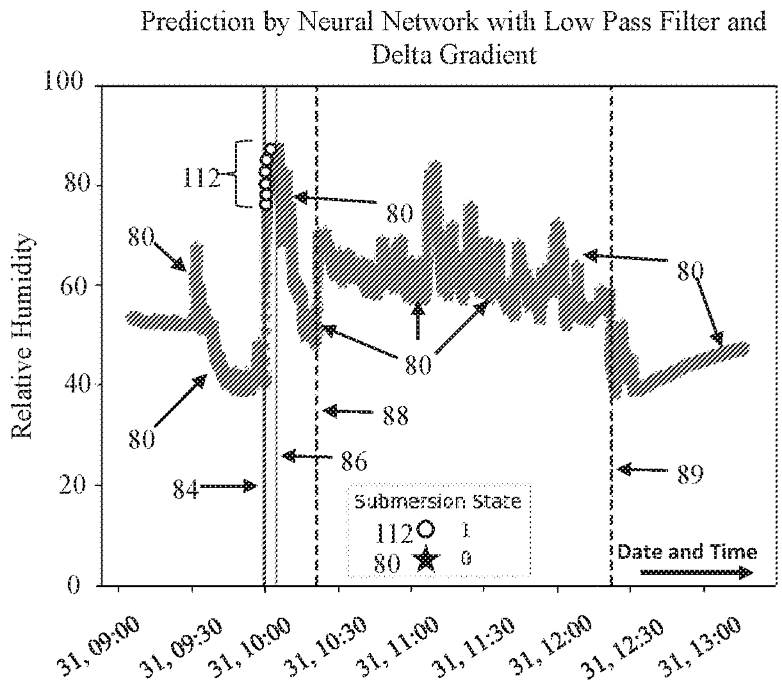
Prediction by Neural Network with Low Pass Filter and
Delta Gradient
Relative Humidity
100
80
60
40
20
0
112
80
80
80
80
80
84
86
88
89
Submersion State
112 1
80 0
Date and Time
31, 09:00
31, 09:30
31, 10:00
31, 10:30
31, 11:00
31, 11:30
31, 12:00
31, 12:30
31, 13:00

FIG. 8B

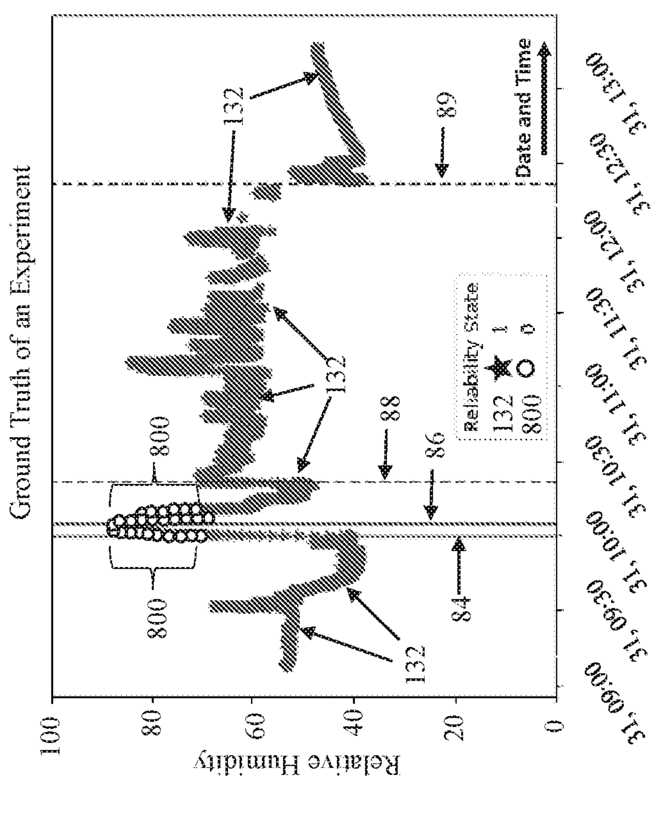
Ground Truth of an Experiment
Relative Humidity
100
80
60
40
20
0
31, 09:00
31, 09:30
31, 10:00
31, 10:30
31, 11:00
31, 11:30
31, 12:00
31, 12:30
31, 13:00
Date and Time
800
800
132
132
132
132
84
86
88
89
Reliability State
132 1
800 0

FIG. 9A

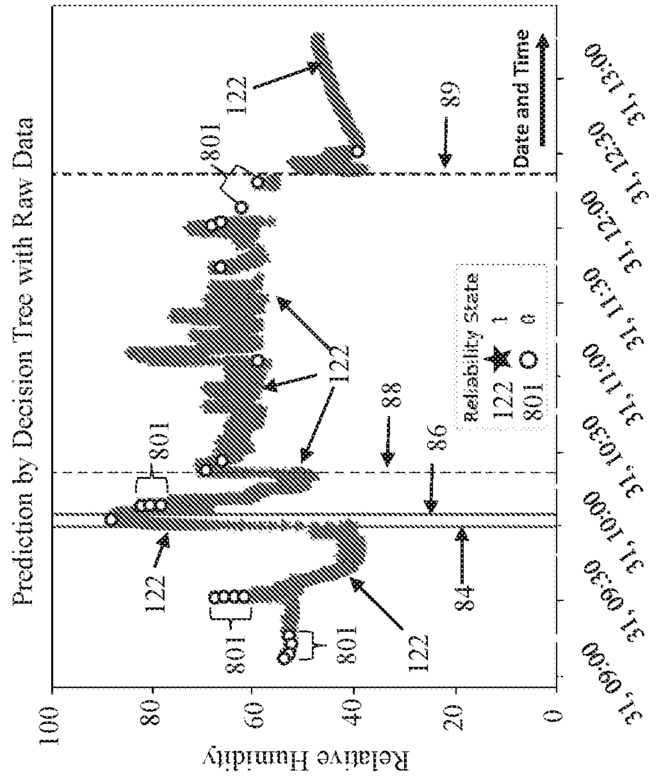
Prediction by Decision Tree with Raw Data
Relative Humidity
100
80
60
40
20
0
31, 09:00
31, 09:30
31, 10:00
31, 10:30
31, 11:00
31, 11:30
31, 12:00
31, 12:30
31, 13:00
Date and Time
801
801
801
801
122
122
122
122
122
84
86
88
89
Reliability State
122 1
801 0

FIG. 9B

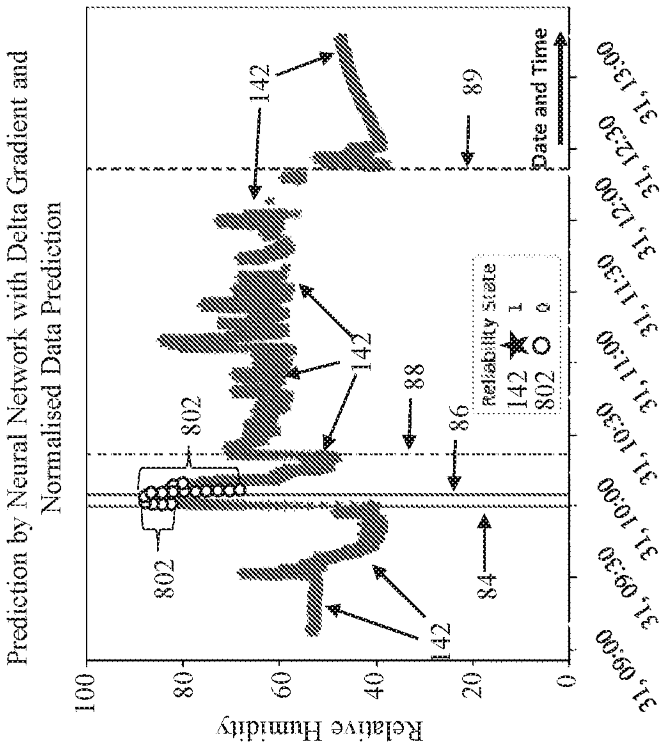

FIG.10A

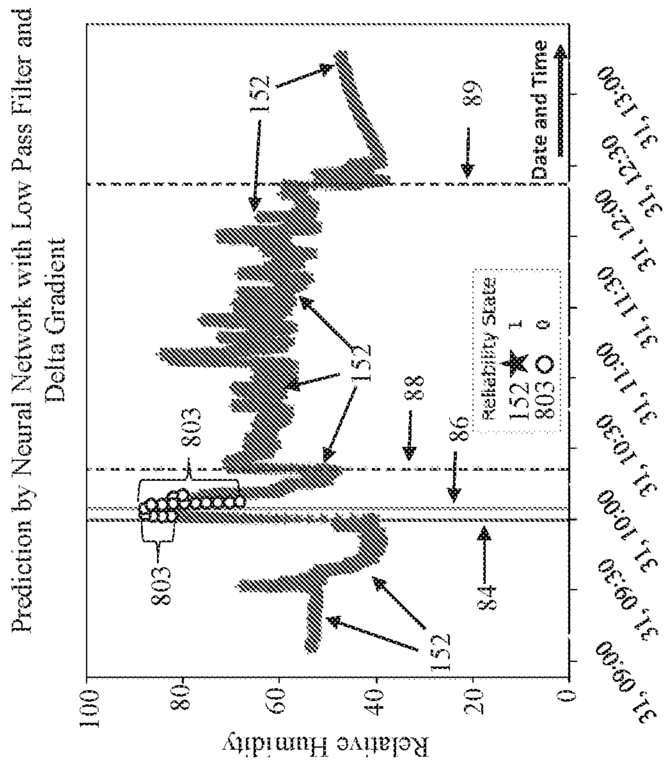

FIG.10B

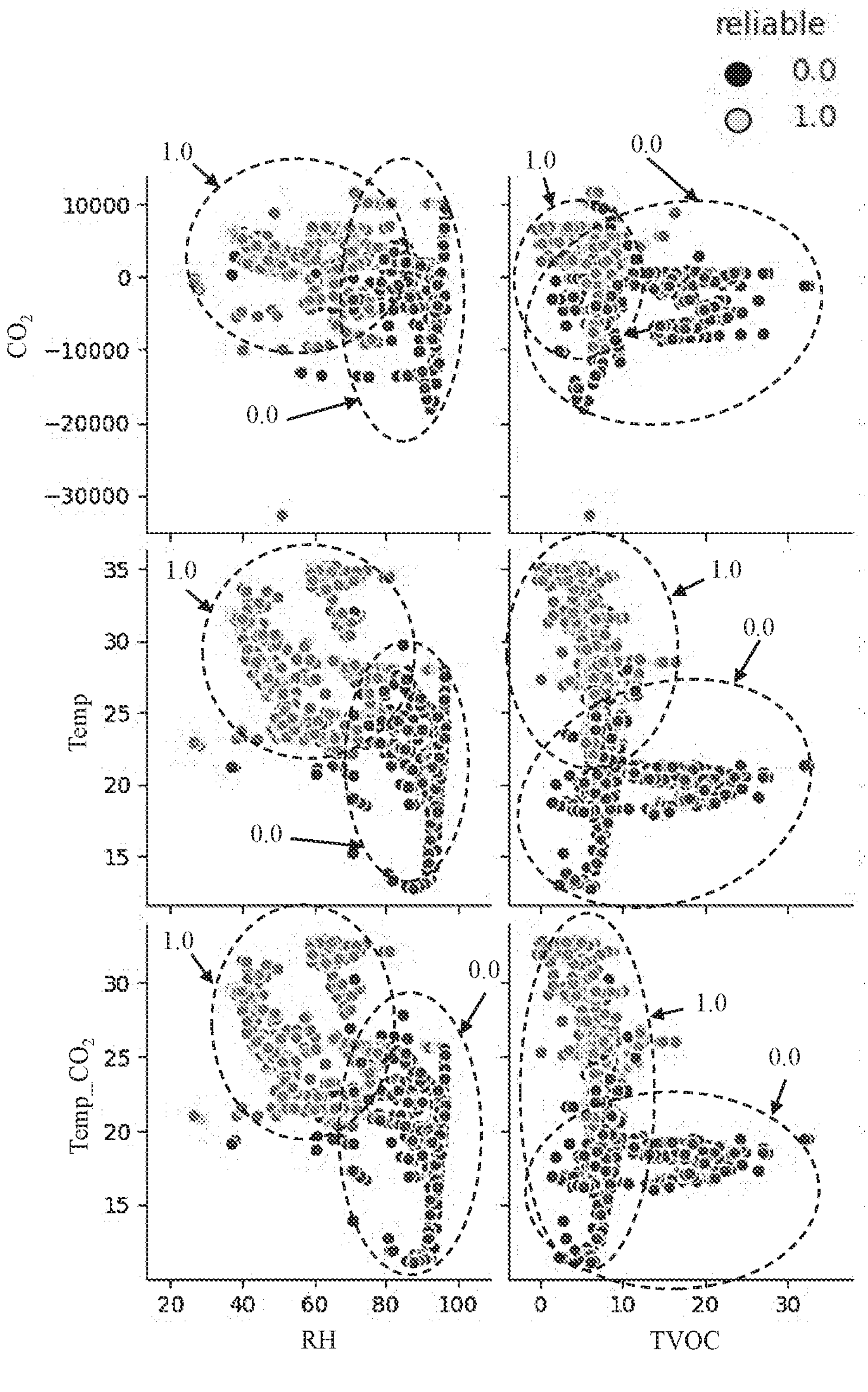
reliable
0.0
1.0
1.0
0.0
1.0
0.0
1.0
0.0
1.0
0.0
1.0
0.0
1.0
0.0
CO2
Temp
Temp_CO2
RH
TVOC
10000
0
−10000
−20000
−30000
35
30
25
20
15
30
25
20
15
20
40
60
80
100
0
10
20
30

FIG.11A

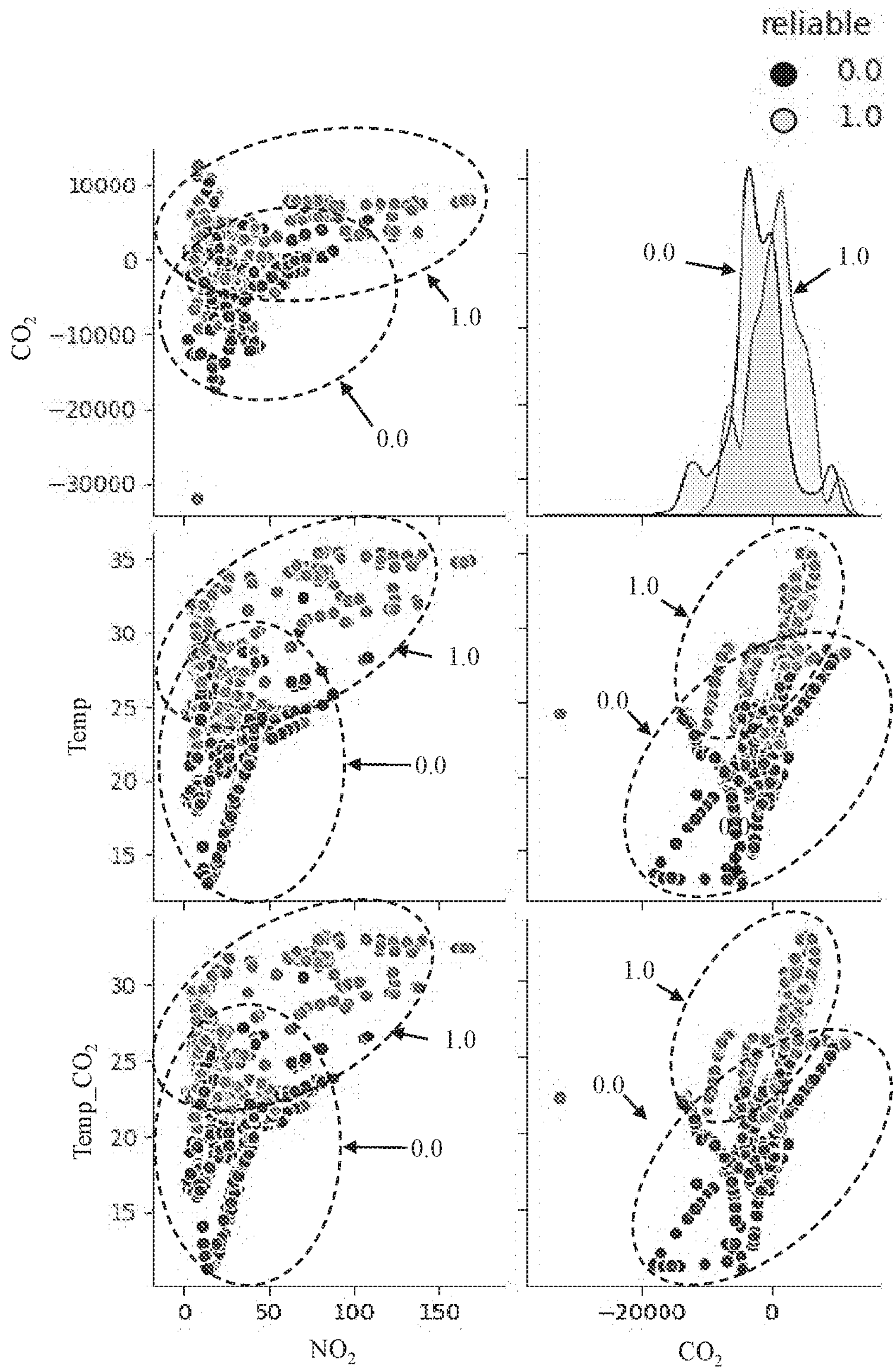
reliable
0.0
1.0
CO_2
Temp
Temp_CO_2
NO_2
CO_2
10000
0
−10000
−20000
−30000
35
30
25
20
15
0
50
100
150
−20000
0.0
1.0

FIG.11B

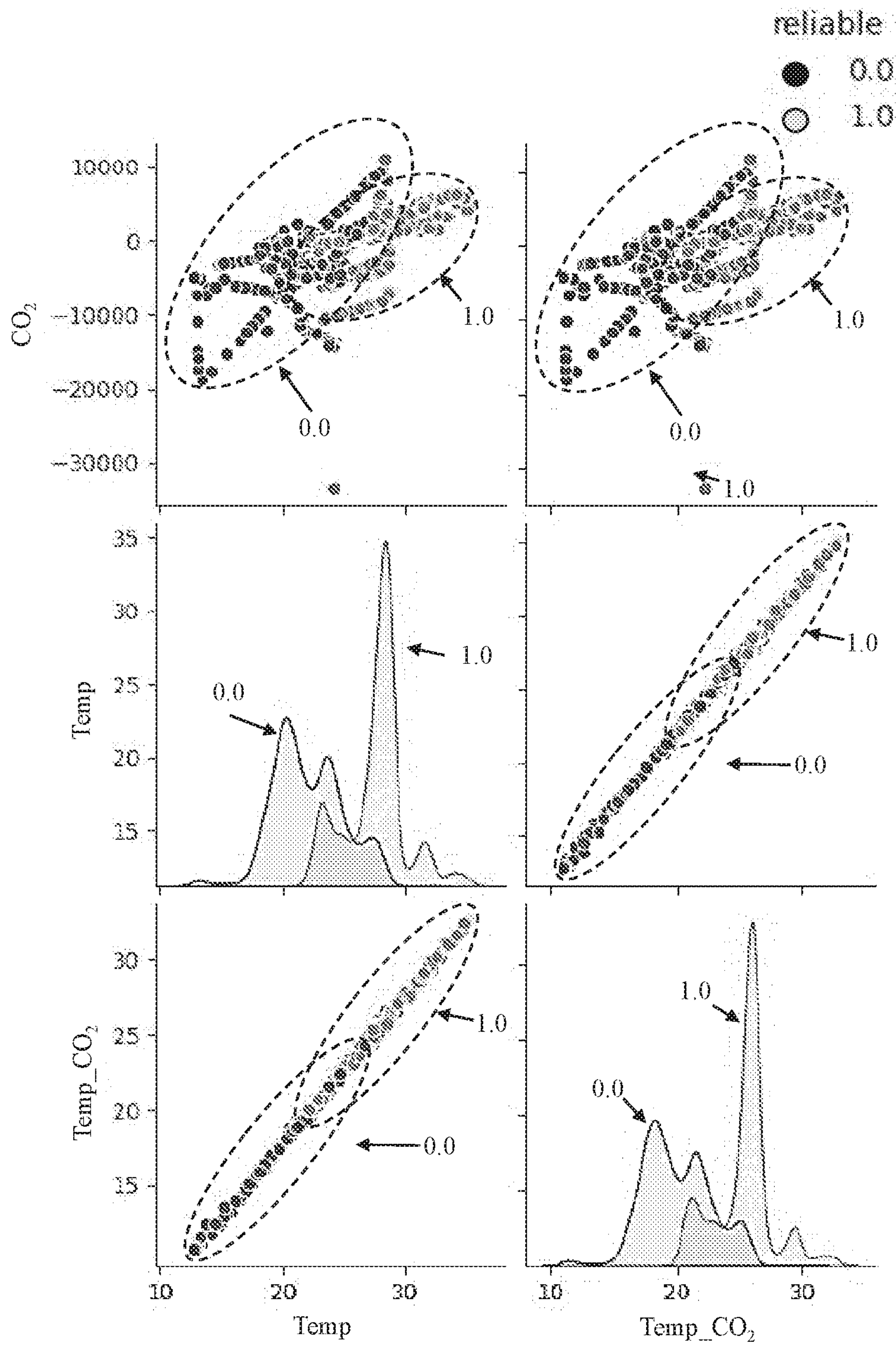
reliable
0.0
1.0
10000
0
−10000
−20000
−30000
CO_2
1.0
0.0
1.0
0.0
1.0
35
30
25
20
15
Temp
0.0
1.0
1.0
0.0
30
25
20
15
$Temp\_CO_2$
1.0
0.0
1.0
0.0
10
20
30
Temp
10
20
30
$Temp\_CO_2$

FIG.11C

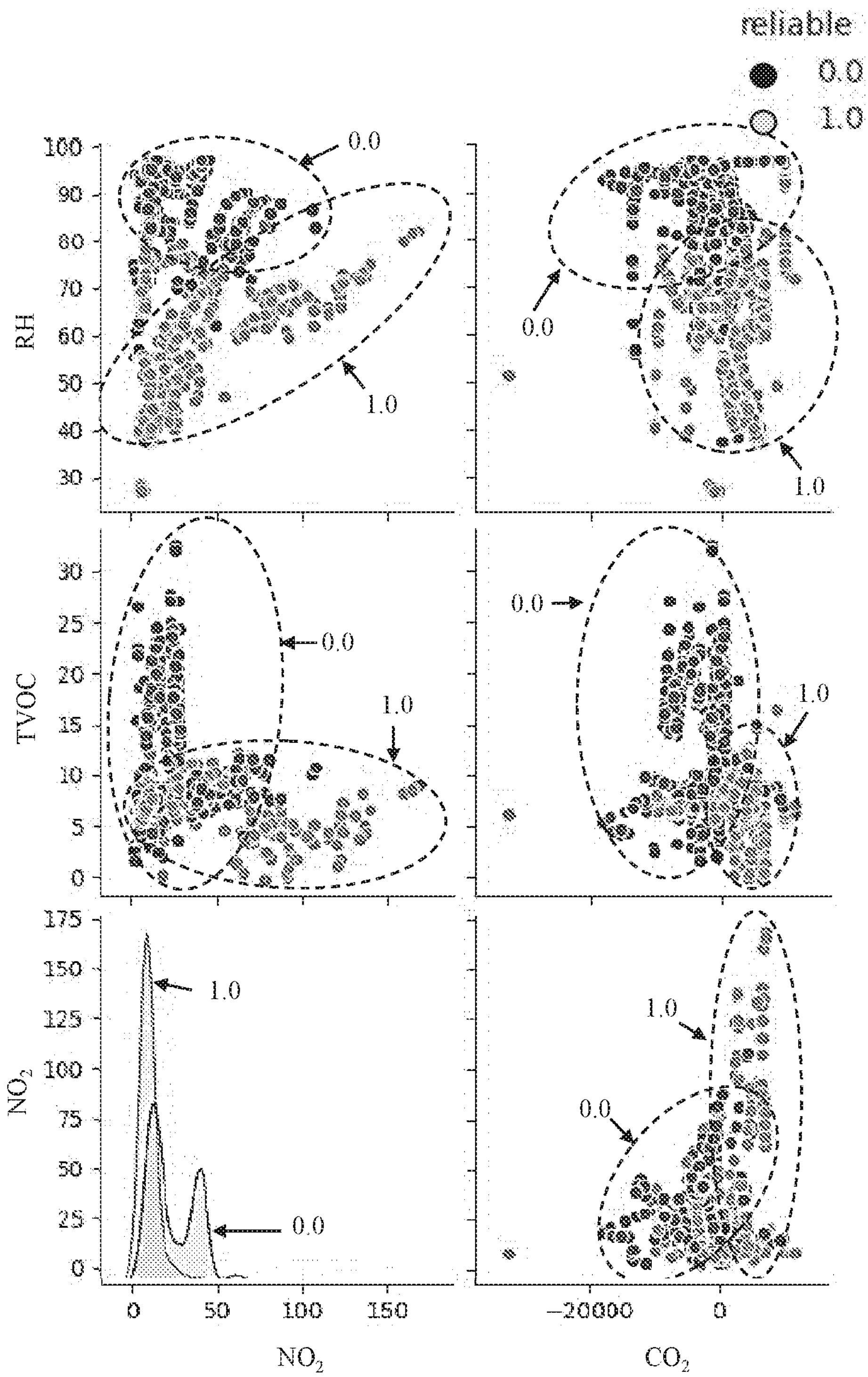
reliable
0.0
1.0
RH
TVOC
NO2
NO2
CO2
0.0
1.0
0.0
1.0
0.0
1.0
0.0
1.0
1.0
0.0
1.0
0.0

FIG.12A

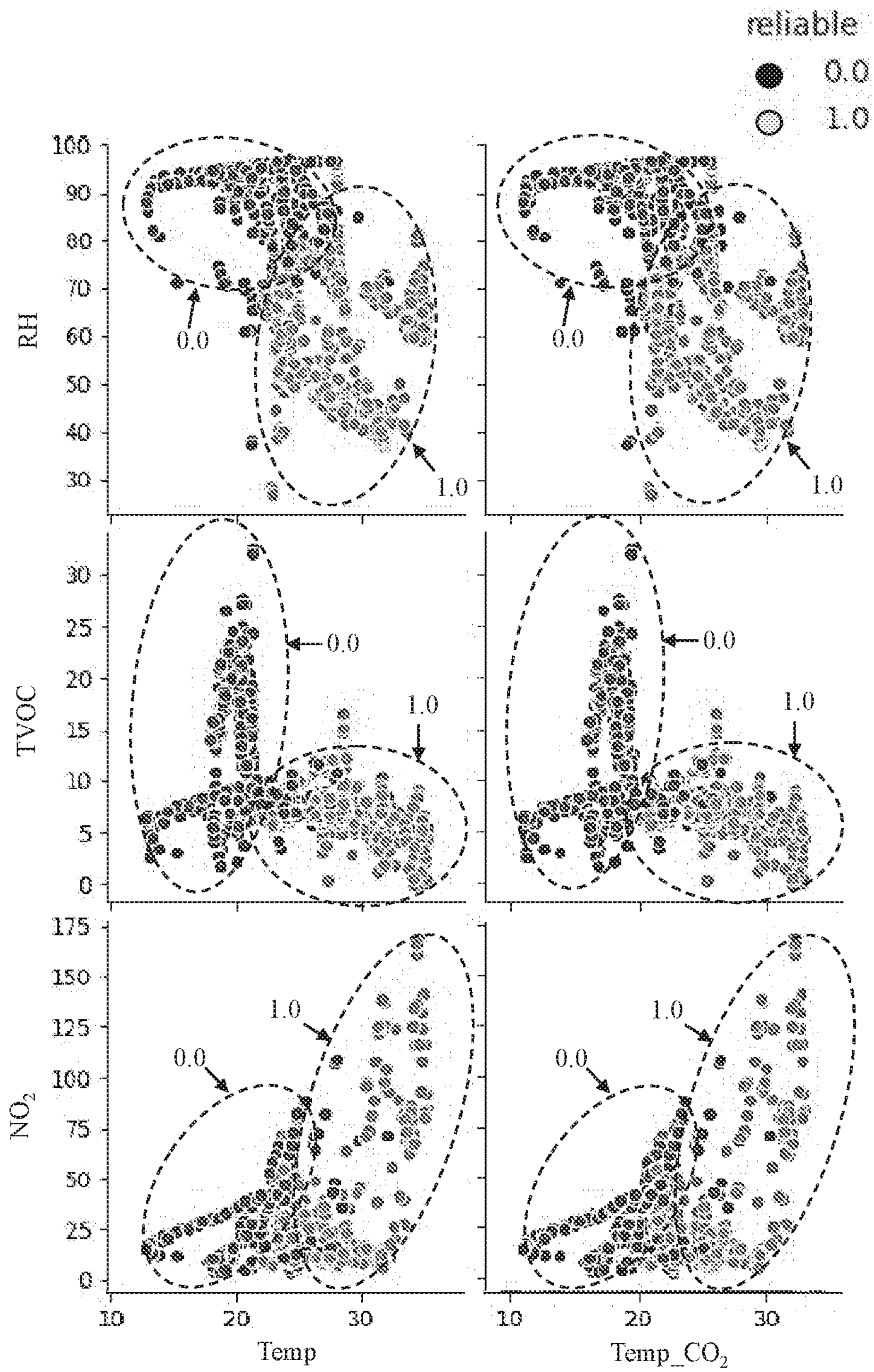
reliable
0.0
1.0
RH
TVOC
NO_2
Temp
$Temp\_CO_2$
0.0
1.0
0.0
1.0
0.0
1.0
10 20 30
100 90 80 70 60 50 40 30
30 25 20 15 10 5 0
175 150 125 100 75 50 25 0

FIG.12B

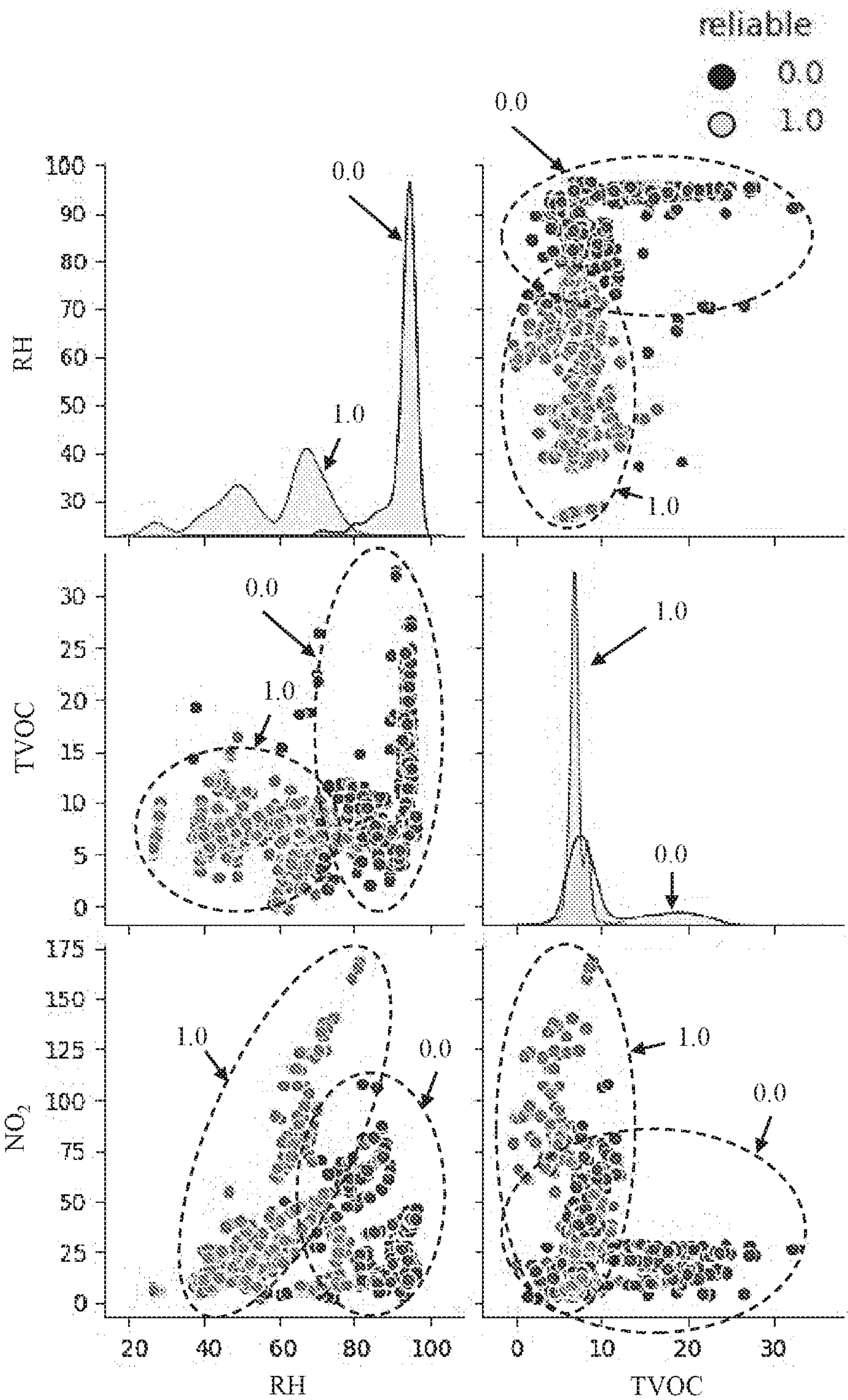
reliable
0.0
1.0
0.0
1.0
0.0
1.0
0.0
1.0
1.0
0.0
1.0
0.0
1.0
0.0
RH
TVOC
NO_2
RH
TVOC
100
90
80
70
60
50
40
30
35
30
25
20
15
10
5
0
175
150
125
100
75
50
25
0
20
40
60
80
100
0
10
20
30

FIG.12C

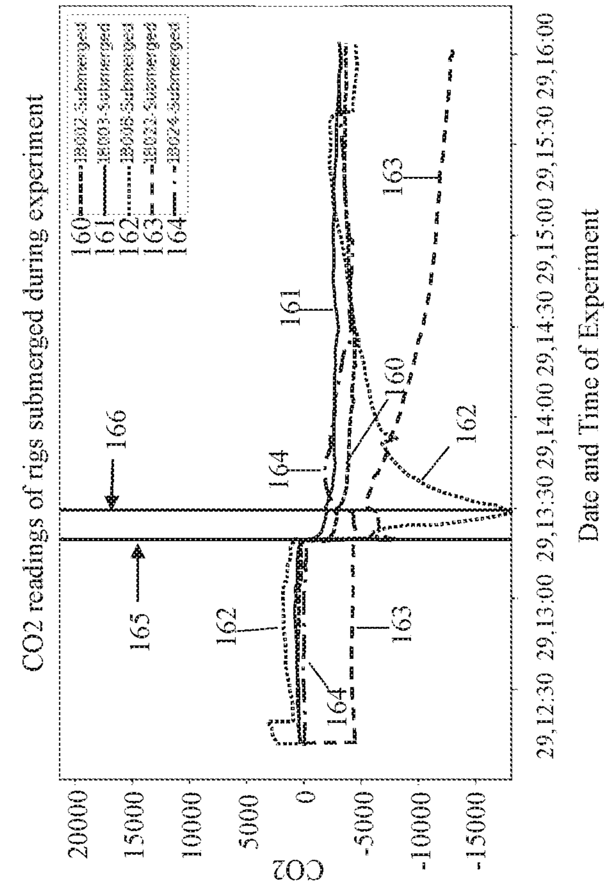

FIG.13A

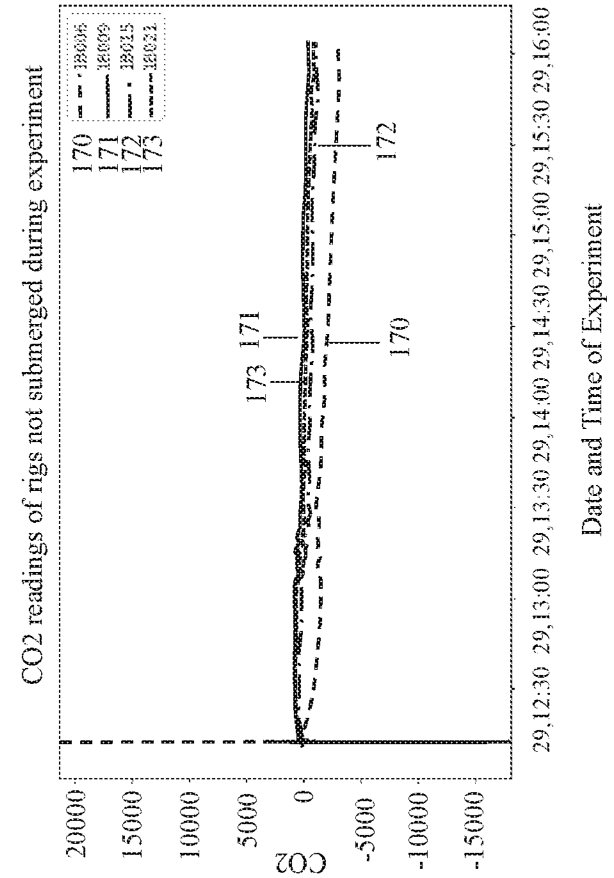

FIG.13B

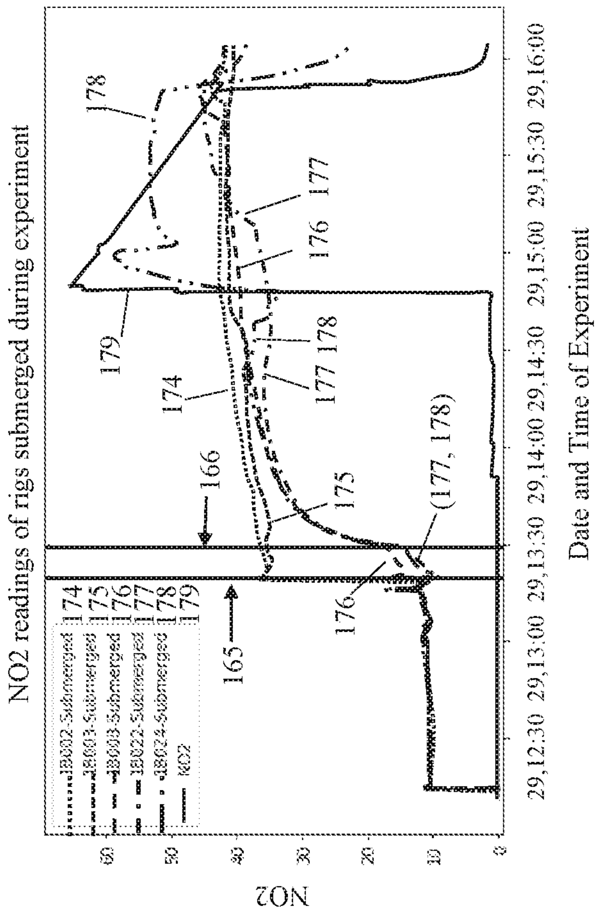

FIG.14A

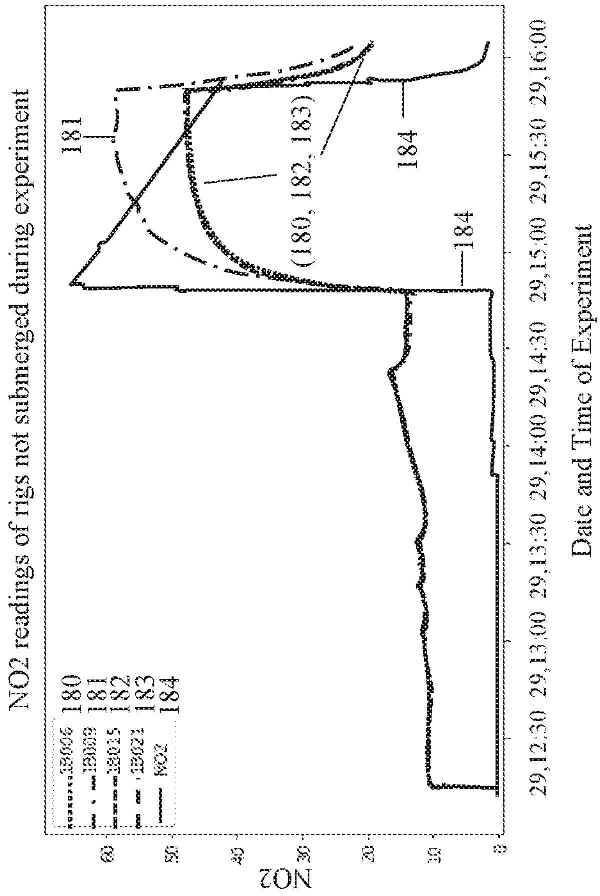

FIG.14B

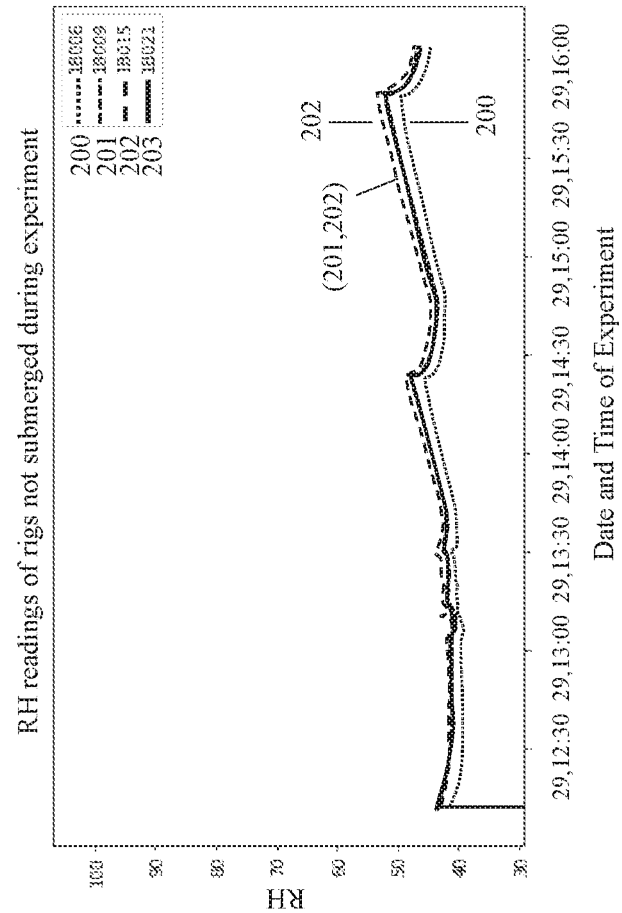

FIG.15B

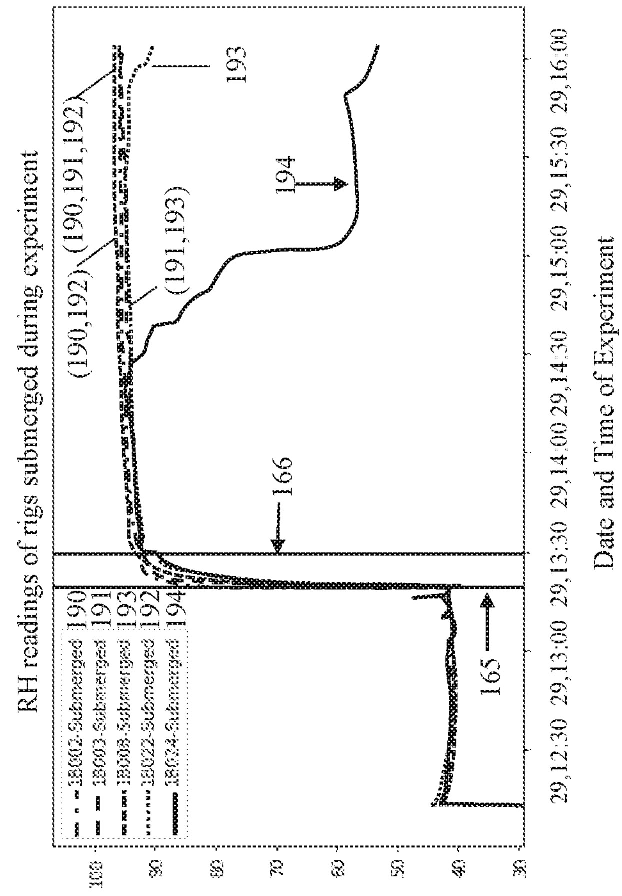

FIG.15A

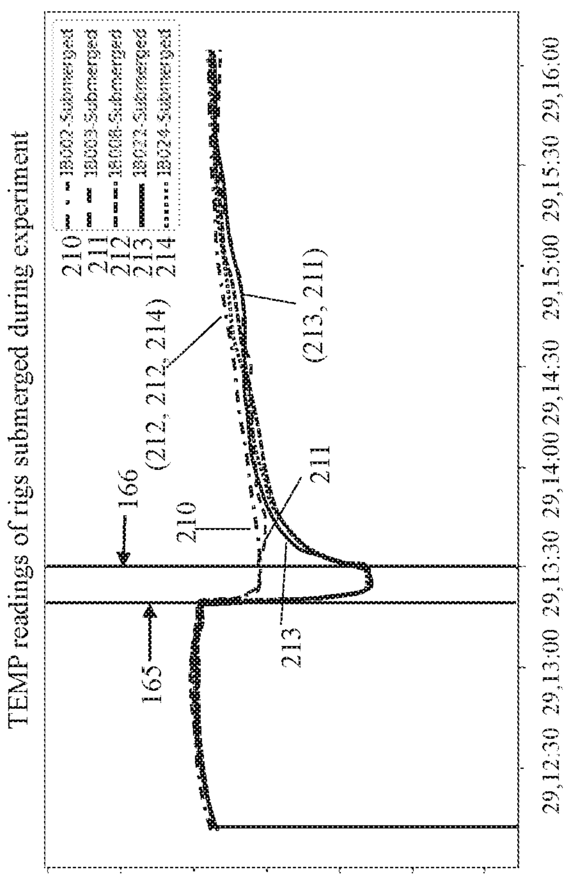

FIG.16A

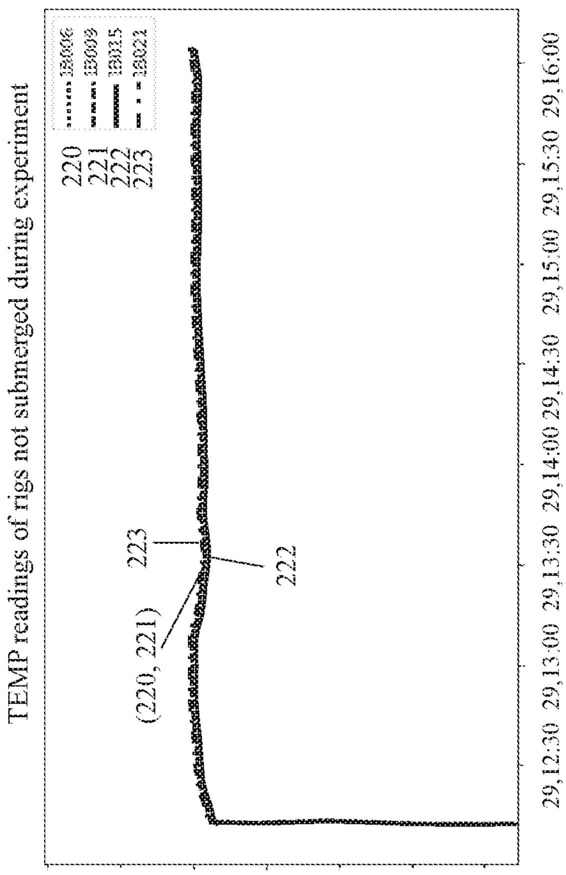

FIG.16B

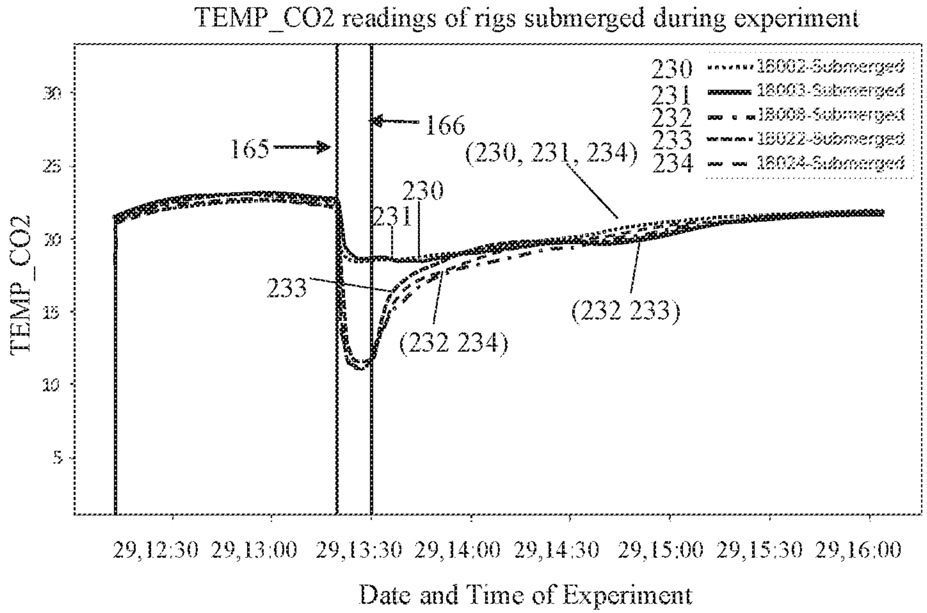

FIG.17A

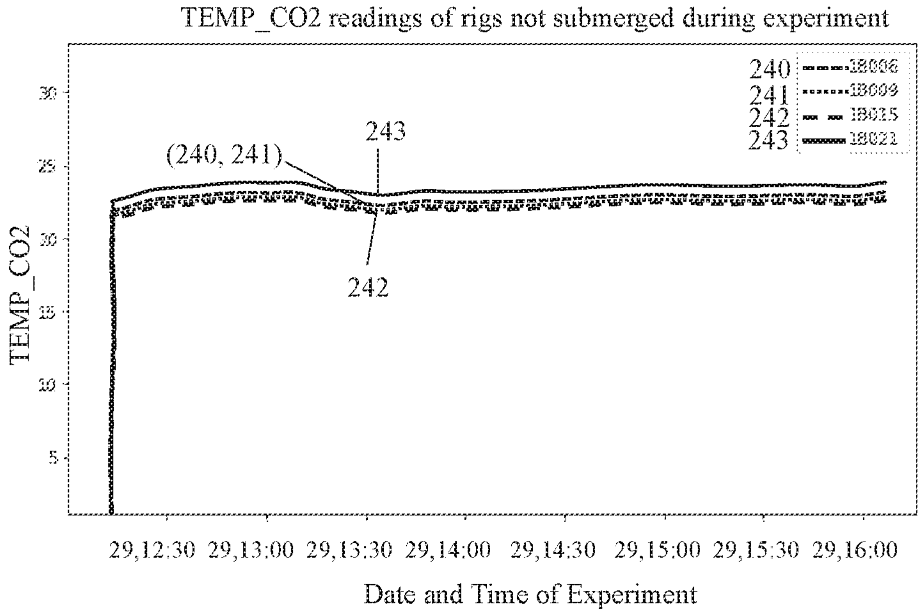

FIG.17B

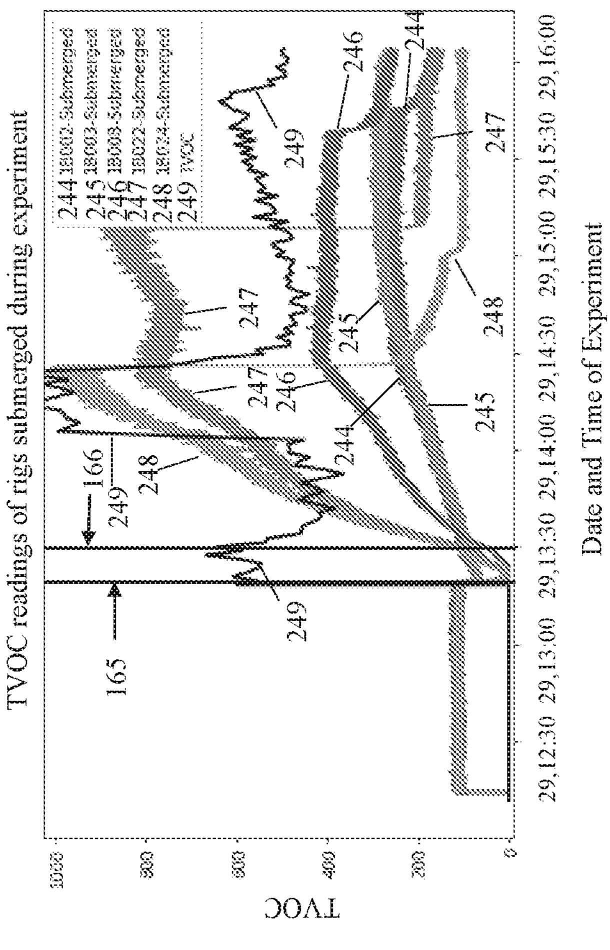

FIG.18A

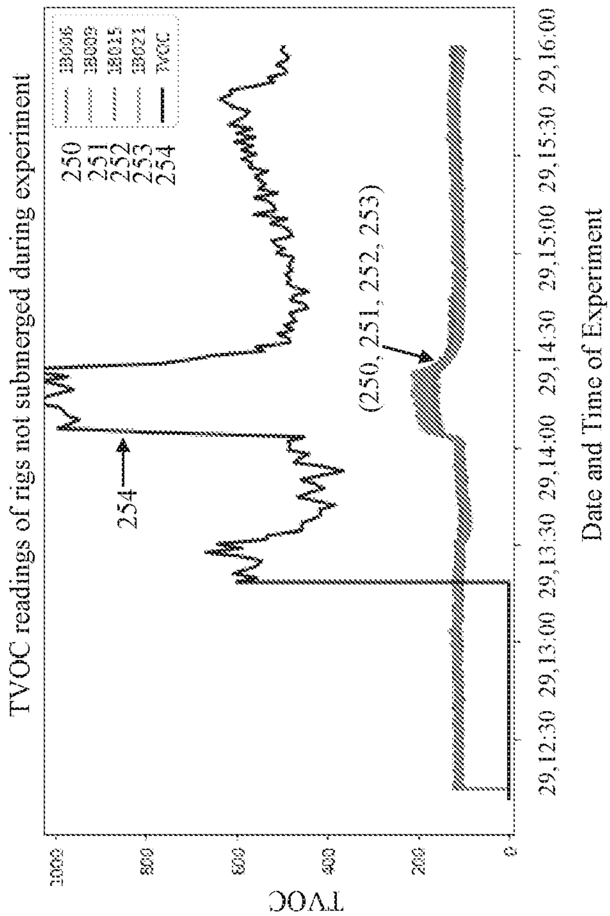

FIG.18B

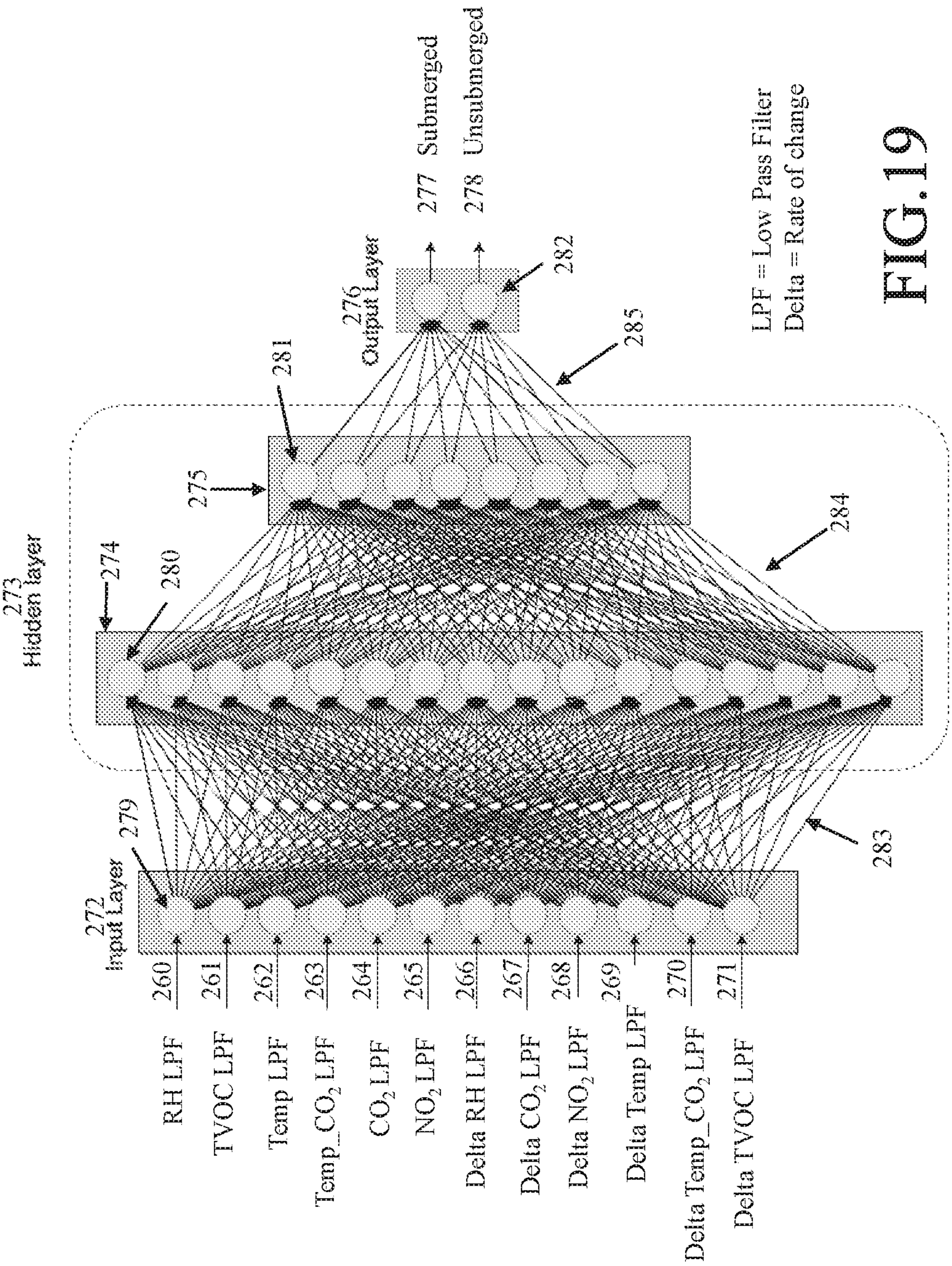
RH LPF 260
TVOC LPF 261
Temp LPF 262
Temp_CO_2 LPF 263
CO_2 LPF 264
NO_2 LPF 265
Delta RH LPF 266
Delta CO_2 LPF 267
Delta NO_2 LPF 268
Delta Temp LPF 269
Delta Temp_CO_2 LPF 270
Delta TVOC LPF 271
272 Input Layer
279
283
273 Hidden layer
274
280
275
281
284
285
276 Output Layer
282
277 Submerged
278 Unsubmerged
LPF = Low Pass Filter
Delta = Rate of change

FIG.19

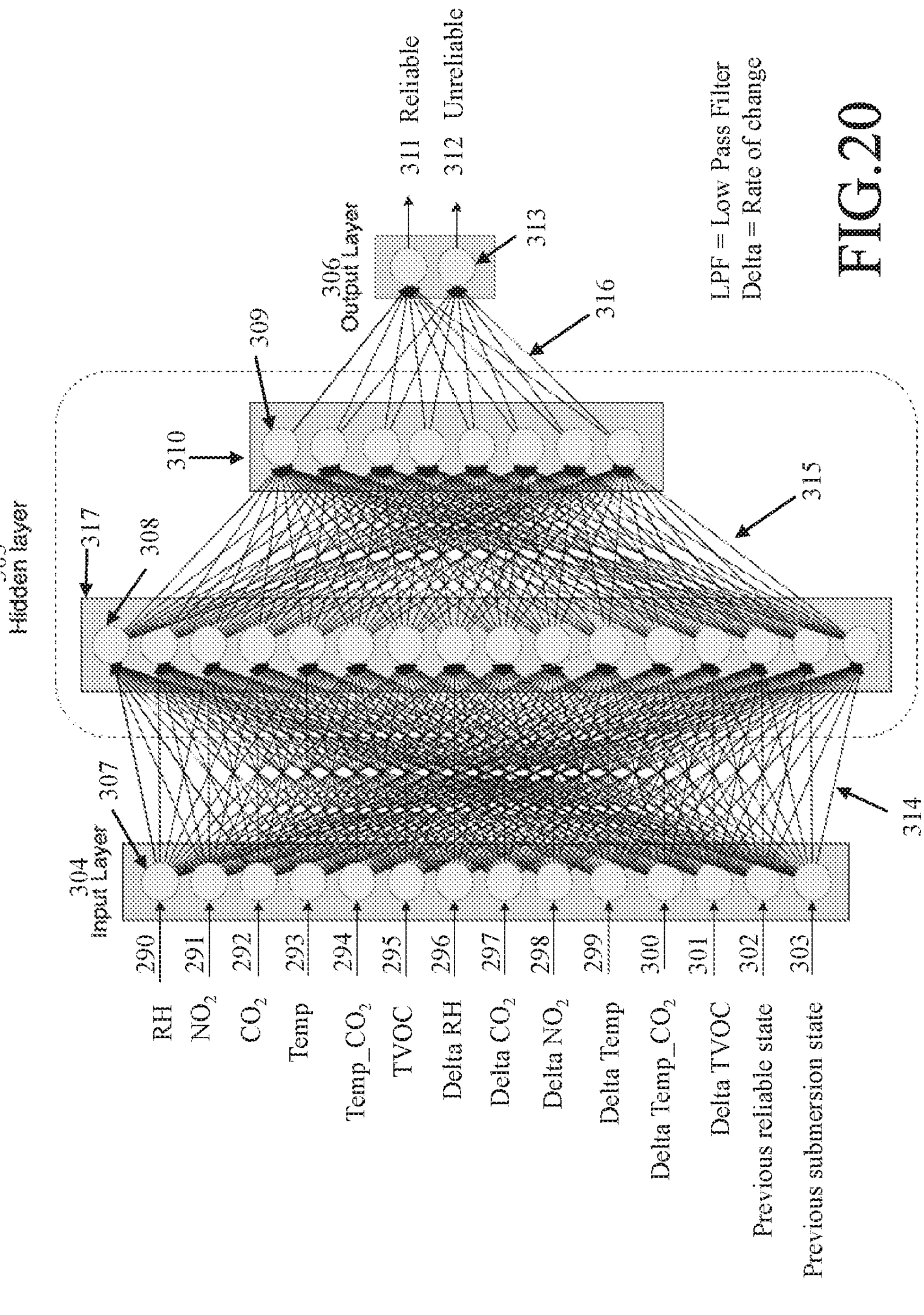
RH
NO_2
CO_2
Temp
Temp_CO_2
TVOC
Delta RH
Delta CO_2
Delta NO_2
Delta Temp
Delta Temp_CO_2
Delta TVOC
Previous reliable state
Previous submersion state
290
291
292
293
294
295
296
297
298
299
300
301
302
303
304
Input Layer
307
314
305
Hidden layer
317
308
310
309
315
316
306
Output Layer
313
311 Reliable
312 Unreliable
LPF = Low Pass Filter
Delta = Rate of change

FIG.20

INTERNATIONAL SEARCH REPORT

International application No
PCT/IB2024/052057

A. CLASSIFICATION OF SUBJECT MATTER
INV. G01N33/00 G06N20/00
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)
G01N 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

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	US 2019/257803 A1 (BROWN MICHAEL K [US] ET AL) 22 August 2019 (2019-08-22) paragraph [0003] paragraph [0014] figure 1 paragraph [0020] paragraph [0026] -----	1-20
Y	CN 112 098 600 A (HARBIN INST TECHNOLOGY) 18 December 2020 (2020-12-18) figure 1 -----	1-20

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

☒ See patent family annex.

* Special categories of cited documents :

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"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

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"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
28 May 2024	06/06/2024

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	D'Inca, Rodolphe

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INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/IB2024/052057

Patent document cited in search report		Publication date	Patent family member(s)	Publication date
US 2019257803	A1	22-08-2019	NONE	
CN 112098600	A	18-12-2020	NONE	