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(54) **NEUROCOMPUTATIONAL ELECTROCHEMICAL SENSING DEVICE FOR PREDICTING PROPERTIES OF A SUBSTANCE**

(57) A neurocomputational electrochemical sensing device (1) is proposed for predicting properties of a substance. The device (1) comprises: a plurality of electrochemical sensors constituting a sensor array (3), the sensors being sensitive to sensed attributes advantageous to predict a set of properties of interest of the substance, each sensor being configured to output a sensor output signal indicative of a sensor response of the respective sensor to measurable changes in the sensed attributes of the substance; a readout circuit (5) for biasing the sensors and for conditioning the sensor output signals into readout circuit output signals to facilitate further processing of the sensor responses; and an artificial neural network processor (7) for processing the readout circuit output signals, the processor (7) comprising neurons interconnected by synapses, the processor (7) being configured to output a set of processor output signals whose signal values are indicative of the properties to predict. The sensor array (3) comprises first electrochemical sensors selective to properties correlated with the desired properties to predict, and second electrochemical sensors sensitive primarily to the main interferences of the substance. The neurons and/or the synapses are configured to be trained to compensate for sensor drift and/or cross-sensitivities upon generating the processor output signals.

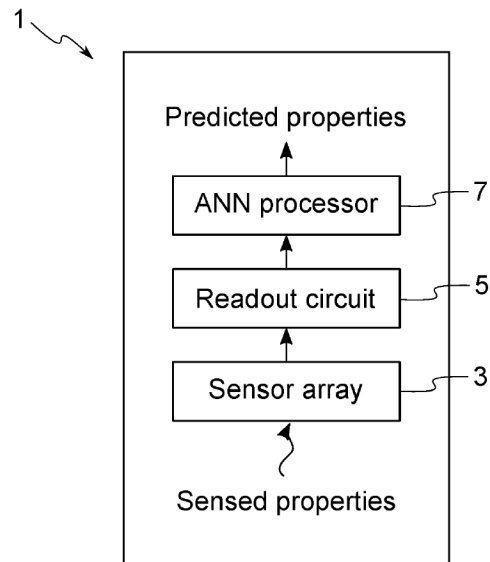


Fig. 1

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Description

TECHNICAL FIELD

[0001] The present invention relates to a neurocomputational electrochemical sensing device, such as a transistor-based sensing device, for predicting dynamic (bio)chemical properties (i.e. dynamic properties which are chemical and that may relate to processes occurring within living organisms) of a substance. The device comprises an artificial neural network processor that is configured to be trained to compensate for sensor drift and cross-sensitivities. The invention equally relates to a method of operating the sensing device.

BACKGROUND OF THE INVENTION

[0002] Conceived to sense and qualify biological and chemical information beyond human capabilities, biochemical analytical systems are in rising demand to assist societies in applications like health, food safety, and environmental protection. The need to prevent and control critical situations in situ/vivo and in real time has pushed transduction into the nanoscale, packing multiple sensors into miniaturised, fast lab-on-a-chip designs. As sensors' density increases, their outputs grow in redundancy, complementariness, and dimensionality. However, with downscaling, noise increases while stability decreases. Such effects add to selectivity restraints long endured by chemical detectors, impairing the reliability of latest microanalytical integrations.

[0003] Among sensor alternatives, microelectrodes and field-effect transistors (FETs) fabricated in semiconductor technologies present advantages such as miniaturisation, mass fabrication, and easy integration with readout electronic circuitry that make them particularly suitable for incorporation into arrays for on-site measurements. Even though these devices are sensitive enough for a wide range of healthcare (e.g. bio-fluid analysis), environmental (e.g. water quality monitoring), and industrial (e.g. food quality control) applications, their commercial application in such settings is conditioned on aging and cross-sensitivities that can severely impair the reliability of the device. Aging is mainly caused by fouling and drifts due either to substance migration into or out of the sensing surface, or to surface hydration. Cross-sensitivity to temperature and interfering species can also constrain the reliability of the measurements, especially when the sensors operate in the field, out of a controlled experimental setup.

[0004] In this context, chemometrics is a promising tool to boost accuracy of the measurements and to translate them into actual biochemical knowledge discovery. By modelling the underlying relationships and structure between the measured properties of the chemical system, cross-sensitivity in sensor measurements can be exploited to calibrate for non-idealities, such as temperature, aging or contamination by other chemical species. These

same models can be further used to predict complex biochemical parameters, to classify future samples, and to identify critical episodes. Classical chemometric solutions run analytics offline, trained on data batches containing steady-state responses or complete measurement cycles of the sensor array. In order to facilitate machine learning, input data is usually transformed into an intermediate space by means of unsupervised (e.g. principal component analysis (PCA), self-organising maps, t-distributed stochastic neighbour embedding) or supervised (e.g. partial least squares) approaches. Linear and non-linear algorithms, such as discriminant analysis, k-means, k-nearest neighbours, support vector machines and random forests, run in a succeeding step to predict categorical or real-valued variables in the big biochemical data. Deep artificial neural networks (ANNs) provide scalable multilayer representations to fit the complexity of the problem in a single model, at the cost of strong computational requirements.

[0005] Most chemometrics, and especially deep ANN solutions, run aside on highspeed clocked, synchronous computers. Because most current integrated measuring devices read out the level of every analyte separately, storage and processing bottlenecks arise at the posterior processing stages. This results in higher latencies, higher energy consumption and limited miniaturisation.

[0006] On- and off-chip compensation methods have been proposed to overcome some of the above challenges to some extent. However, none of the former approaches addresses, for example, sensor cross-sensitivity to chemical and thermal interferences on-chip when monitoring continuous readings from the sensor array. Thus, the wide adoption of these analytical systems for industrial applications is still limited mainly due to sensor non-idealities, and due to the restricted deployability of these devices in terms of compactness and energy autonomy.

[0007] Current online (bio)chemical monitoring devices are generally expensive, bulky, non-predictive, limited to a fix set of a few properties, and require periodical calibration in front of environmental changes. Measurements not feasible with such specific equipment are conducted in laboratories with high associated costs and delays. If predictive models are used, then they are deployed in the cloud. This translates into privacy concerns and, again, into latencies due to data transmission, and additional storage and processing bottlenecks that accentuate as the volume of information accumulates over time.

SUMMARY OF THE INVENTION

[0008] The objective of the present invention is thus to overcome at least some of the above limitations relating to bio(chemical) analytical systems.

[0009] According to a first aspect of the invention, there is provided a neurocomputational electrochemical sensing device for predicting properties of a substance as

recited in claim 1.

[0010] The proposed device integrates a plurality of electrochemical sensors (e.g. solid-state electrochemical microsensors), which are sensitive to attributes advantageous to predict a set of properties of interest of the sensed substance, and which operate together with a readout circuit and an ANN processor. The readout circuit biases the sensors and converts their responses into signals conditioned to facilitate subsequent ANN processing into predictions of (bio)chemical properties of interest. The sensors, the readout circuit, and/or the ANN processor can be integrated in a common system substrate (e.g. silicon). The electrochemical sensing device may also integrate automated, miniaturised fluidics (e.g. micro-/nano-fluidics) to achieve precise manipulation and control of fluids and high-throughput analysis with low volume of fluids, chemicals, and reagents.

[0011] The proposed electrochemical-sensing analytical device provides at least some of the following advantages:

Reliability: The invention provides self-calibrated correction of multiple sensor non-idealities (e.g. aging, cross-sensitivities) in order to lengthen sensor lifetime when operating outside of controlled laboratory settings.

[0012] Miniaturisation: solid-state electrochemical (e.g. field-effect transistor (FET), microelectrodes) microsensors and processing circuits can be easily integrated in standard complementary metal-oxide-semiconductor (CMOS) very large-scale integration (VLSI) technologies.

[0013] Low cost: The present invention enables solid-state electrochemical monitoring, designed for cost-effective mass manufacturability at wafer level using standard CMOS electronic integration technologies.

[0014] Energy efficiency: The device is configured to carry out efficient, local readout encoding as early relevant features to facilitate prediction of target attributes. Signal processing in continuous time is also enabled to avoid redundant information and computation cycles, according to the dynamics of input signals and neural network, not at a fixed frequency provided by an external clock.

[0015] The present invention thus solves the technical problem of fabricating multiparametric analytical devices capable of precise sensing, capable of operating in tiny/mobile locations and in real time, and capable of predicting multiple ad-hoc parameters at low maintenance costs.

[0016] According to a second aspect of the invention, there is provided a method of operating the device as recited in claim 14.

[0017] Other aspects of the invention are recited in the dependent claims attached hereto.

BRIEF DESCRIPTION OF THE DRAWINGS

[0018] Other features and advantages of the invention will become apparent from the following description of

non-limiting example embodiments, with reference to the appended drawings, in which:

- Figure 1 shows a simplified block diagram illustrating a high-level system setup of the proposed device;
- Figure 2 shows an ANN pre-processor implementation according to a first embodiment, and which is based on amperometric sensing using FETs;
- Figure 3 shows an ANN pre-processor implementation according to a second embodiment, and which is based on potentiometric sensing using FETs;
- Figure 4 shows an ANN pre-processor implementation according to a third embodiment, and which is based on amperometric sensing using three electrodes per sensor;
- Figure 5 shows an ANN pre-processor implementation according to a fourth embodiment, and which is based on potentiometric sensing using two electrodes per sensor;
- Figure 6 schematically illustrates a first example implementation of the neurocomputational electrochemical sensing device;
- Figure 7 schematically illustrates a second example implementation of the neurocomputational electrochemical sensing device; and
- Figure 8 is a flow chart illustrating the method of operating the neurocomputational electrochemical sensing device according to an example of the present invention.

DETAILED DESCRIPTION OF EMBODIMENTS OF THE INVENTION

[0019] Some embodiments of the present invention will now be described in detail with reference to the attached figures. The non-limiting embodiments are described in the context of an electrochemical analysis (e.g. environmental/sanitary monitoring, health assessment from markers in biofluids, chemical process monitoring) of a substance, which in the present embodiments is a liquid. Identical or corresponding functional and structural elements which appear in different drawings are assigned the same reference numerals. It is to be noted that the use of words "first" and "second" may not imply any kind of particular order or hierarchy unless such order or hierarchy is explicitly or implicitly made clear in the context.

[0020] Figure 1 shows a high-level system setup of the proposed electrochemical sensing device 1 for predicting properties of a substance, which in this example is a liquid. As depicted, the device comprises a plurality of electrochemical sensors forming a sensor array 3, where the

sensors are sensitive to sensed attributes advantageous to predict a set of properties of interest of the substance, and that operate together with a readout circuit 5 and an ANN processor 7. The readout circuit biases the sensors and reads or transforms sensor responses to measurable changes in the sensed attributes into signals conditioned to facilitate subsequent ANN processing for predicting (bio)chemical properties of interest. Any one of the sensor array, the readout circuit, and the ANN processor can be integrated in a common system substrate (e.g. silicon). The electrochemical sensing device may also integrate automated, miniaturised fluidics (e.g. micro-/nanofluidics) to achieve precise manipulation and control of fluids and high-throughput analysis with low volume of fluid samples, chemicals, and reagents so as to further reduce analytical costs. Thus, the system substrate may be integrated with the fluidics following a packaging scheme suitable for mass production (e.g. wafer-level production) with proper fluid isolation from electrical I/O signals, and adequate fluidic sealing on top of the system substrate (e.g. silicon or epoxy carriers for silicon system substrates).

[0021] Figure 2 schematically shows the readout circuit 5 together with the sensor array 3 according to the first embodiment. According to this embodiment, the circuit forms an amperometric sensing circuit or element using FETs (e.g. ion-sensitive field-effect transistors (IS-FETs), chemical field-effect transistors (CHEMFETs), and/or biosensor field-effect transistors (BIOFETs)) as sensors 9_1 , 9_2 , 9_3 .

[0022] The sensor array 3 comprises a plurality of sensors that, together with the readout circuit 5, perform as an artificial neural network pre-processor 11 mimicking the functioning or operation of (artificial) synapses and neurons. In Figure 2, all the circuit elements apart from the sensors and the ANN processor 7 form the readout circuit. The following notations are used in Figure 2: D denotes the drain node or terminal of the transistor, S denotes the source node or terminal of the transistor, G denotes the gate node or terminal of the transistor, B denotes the bulk node or terminal of the transistor, I_B denotes the biasing current, I_D denotes the drain current, $I_I = I_B - I_D$, V_G denotes the gate voltage, V_S denotes the source voltage, V_{DS} denotes the drain-to-source voltage, g_m denotes the transconductance of the transistor, and S_i denotes the sensitivity of the sensor, i.e. the numerical relationship between each of the quantifiable sensed properties or analytes the sensors are sensitive to and the electrical signal they are converted to at the sensors.

[0023] Each sensor may be, to a certain extent, selective (i.e. mainly or predominantly sensitive) to a given property of a substance, but may also present some degree of cross-response to other properties sensed in the array. In Figure 2, these different properties are represented by the wavy lines so that each wavy line represents a given property of a liquid to be sensed. For instance, the uppermost wavy line may represent ion A concentration in the liquid to be sensed, the middle wavy

line may represent ion B concentration in the liquid to be sensed, and the bottom wavy line may represent ion C concentration in the liquid to be sensed. For example, a first type of sensor 9_1 may be selective to ion A concentration in the liquid to be sensed, while a second type of sensor 9_2 may be selective to ion B concentration in the liquid, a third type of sensor 9_3 may be selective to ion C concentration in the liquid. All sensors may also be highly sensitive to the temperature of the liquid, and an Nth type of sensor (not shown in Figure 2) could be selective to this property. In Figure 2, the line thickness of the wavy line indicates the degree of sensitivity to a given property so that the thicker the line, the higher the sensitivity is to that property. At the same time, the first type of sensor may also be somewhat sensitive to the other (bio)chemical parameters in the liquid and, in particular, to the ion B concentration and the ion C concentration, while the second type of sensor may also be somewhat sensitive to the ion A concentration and the ion C concentration, and the third type of sensor may also be somewhat sensitive to the ion A and B concentrations. In the example shown in Figure 2, the sensor array includes a first set of first type of sensors (in this example comprising sensors 9_1) selective to properties correlated with the desired properties to predict, but that may also present some degree of cross-sensitivity to other properties of the substance (i.e. interferences), and a second set of second type of sensors sensitive primarily to the main interferences of the substance: sensors 9_2 mainly sensitive (i.e. mainly responsive to) to one of the interferences, and sensors 9_3 mainly sensitive to another one of the interferences. All sensors may also be inherently significantly sensitive to temperature due to the joint electrochemical and solid-state nature of the sensors. The first type of sensors may thus be further sensitive at least to first interferences of the substance and/or second interferences of the substance, and second type of sensors may further be sensitive at least to the properties to predict and/or to the second interferences of the substance.

[0024] The artificial neural network processor 7 and the artificial neural network pre-processor 11 comprise two types of parts: multiple-input, single-output neurons N, connected by single-input, single-output synapses W, where the synapses have a direction associated with them. Readout input synapses 13 can be understood to be multi-property single-input, single-output synapses. All the neurons and synapses may comprise one or more integrator compartments, which are considered to integrate their inputs obeying dynamic equations (e.g. they act as leaky integrator compartments). Thus, in the present description, the synapses and neurons are configured to process their input signals to generate output signals.

[0025] Accordingly, when a signal passes through synapses and/or neurons, the resulting output signal may be considered to be a processed input signal. However, the verb "process" is to be understood broadly in the present description. In other words, the meaning of this

word is understood to encompass any kind of operation applied to a signal. The neurons may transmit their outputs in the digital domain by performing analogue-to-digital conversion through a spike generator (i.e. asynchronous pulse modulation), or in the analogue domain by an analogue representation of their instantaneous firing rate. For the former purpose, the neurons may comprise spike generators 19 as shown in Figure 2. The choice between the analogue and digital output signals depends on whether or not analogue-to-digital conversion is to be performed in the last compartment providing output of the neurons. Neural input signals come from sensed properties or other neurons through the synapses. Both the neurons and synapses can operate dynamically in continuous time (i.e. varying at any time instant) forming together a directed neural network exhibiting continuous-time dynamical behaviour. The ANN pre-processor comprises a sensing network of K readout input synapses 13 with a single integrator compartment, and a connection strength or weight given by the product of the corresponding sensitivity S_i , and an optional subsequent transconductance g_m and/or readout input gain A . The readout input synapses 13 are connected to different readout neurons 15, which in this example are interconnected by readout recurrent synapses 17. The circuit parameters (e.g. g_m , A , poles of compartment filters, etc.) of the artificial neural network pre-processor synapses (W) and/or the artificial neural network pre-processor neurons (N) of the artificial neural network pre-processor 11 can be learned for the neural network to decompose the sensor output signals, i.e. in the configuration of Figure 2 I_i , into informative, discriminating and/or independent features (i.e. individual properties or characteristics of the substance) next to the sensor, as efficient representations to facilitate modelling the dependencies among sensible (bio)chemical properties and to predict new output properties or behaviours of interest. In other words, the artificial neural network pre-processor synapses and/or the artificial neural network pre-processor neurons are configured to decompose the sensor output signals into informative, discriminating and/or independent properties or characteristics of the substance to facilitate modelling dependencies between any combination of sensible (bio)chemical properties and/or teaching signals $y(t)$ representing the signals to predict by the artificial neural network processor (7). This strategy is useful for saving energy in information coding and for enhancing robustness in front of sensor noise, aging, and cross-sensitivities.

[0026] In the neurons and synapses of the artificial neural network processor 7 and the artificial neural network pre-processor 11, learning can be automated by using optimisation methods like gradient descent that minimise a loss computed from a loss function (e.g. Kullback-Leibler divergence, or possible simplified functional equivalents such as cross-entropy, negative log-likelihood, or (root) mean squared error) representing how well observed properties are modelled. Upon generating

the artificial neural network processor output signals $\hat{y}(t)$, sensor drift may be compensated by modelling the temporal evolution of some given teaching signals $y(t)$ - representing the signals to predict by the ANN processor - with respect to sensor output signals subject to temporal drift; cross-sensitivities may be compensated by modelling the underlying temporal relationships between (i) output signals from sensors selective to properties correlated with the desired properties to predict, (ii) output signals from sensors sensitive primarily to the main interferences, and/or (iii) the teaching signals $y(t)$. The teaching signals may be used together with the output signals from the sensors sensitive primarily to the main interferences (ii) when the teaching signals (iii) are available. It is to be noted that the sensor output signals are also used for training, but they are not referred to as teaching signals in the present description. The teaching signals in the present description are only the signals teaching how the outputs should evolve in time. An embodiment of the invention may train neurons and synapses on a dataset collected offline via backpropagation to compute the gradients (or the surrogate gradients in the case of employing non-differentiable spikes as neuron outputs) of the loss function with respect to the circuit parameters. Both parts (i.e. the neurons and synapses) may be fine-trained online by using local plasticity rules to learn their corresponding parameters. For instance, any of the parameters modifying the overall synaptic weights in W could be learned combining homosynaptic Hebbian and heterosynaptic non-Hebbian rules. In periods when the temporal data of the output properties to predict is made available via teaching signals $y(t)$, local plasticity rules could additionally be gated by error signals indicative of the contributions of each dynamical part to a prediction error depending on a difference between the teaching signals $y(t)$, and the predicted ANN processor output signals $\hat{y}(t)$. Local plasticity rules update the parameters of synapses and neurons locally in space and time according to mathematical equations or learning rules which only use variables available in the neurons (e.g. integrated variables equivalent to postsynaptic currents or membrane potentials in biological neurons, pre- and post-synaptic traces, error signals, etc.). In this case, error backpropagation can be approximated by including biologically plausible neural networks with both feedforward and feedback synapses that allow the prediction errors made by the network to propagate in space and time through the network in the form of the aforementioned error signals.

[0027] As can be seen in Figure 2, and besides the sensors, the readout input synapses 13 comprise a biasing circuit or element 21 for biasing the sensors 9_1 , 9_2 , 9_3 . This can be done for example by setting the voltage for a reference electrode 23 that is immersed in the liquid to be sensed, the source voltage V_S , and/or the biasing current I_B . In this manner, the biasing element sets the operating point of the FET. Biasing signals may be set in open or closed loop; in the second case, they depend on any of the electrical signals available at the readout

circuit. The readout input synapses also comprise an integrator filter element 25 for filtering the sensor output signal, which in the example of Figure 2 is I_i , and a given gain A 27 (which in this example is the gain mentioned above). It is to be noted that the gain A may be given by the same filtering element. The readout recurrent synapses 17 comprise one or more integrator compartments, which each are composed of an integrator filter element 25 with gain A 27, and optionally also summation elements 29 to combine the multiple compartments. The readout neurons 15, on the other hand, also comprise one or more integrator compartments, which each are composed of a summation element 29 to sum up the neural input signals and/or neuron biases (i.e. constant input values), an integrator filter element 25 with gain A 27, and optionally also of a spike generator 19 configured to generate a pulse when its input exceeds a given threshold, and/or additional summation elements 29. In the present embodiment, the compartment of the readout neurons 15 always includes a summation element 29 to sum up the neural input signals. In the configuration of Figure 2, the readout neurons 15 and the readout recurrent synapses 17 comprise only one integrator compartment, but one or more of the neurons 15 and the readout recurrent synapses 17 could comprise a plurality of them where any compartment may be in a feedforward/feed-back loop configuration by addition of more summation elements, or in a series configuration. The outputs of the readout input synapses 13 and the readout recurrent synapses 17 are connected to the readout neurons 15. The outputs of the readout neurons 15, which form readout circuit output signals, are in this example fed to the ANN processor 7. As was mentioned above, in the example of Figure 2, the sensors are FETs, where the reference electrode 23 is configured to be in contact with the solution to be sensed, and configured to set an electric bulk potential in the solution. A sensing layer of the FET interacts with the solution comprising analytes for generating a potential change at the gate insulator surface dependent upon the concentration of the analytes in the solution and the sensitivity S_i to each analyte. The current through the transistor will change according to such potential and to the transconductance g_m of the transistor. The solution to be sensed may thus be understood to be part of the gate of the FETs.

[0028] The configuration of Figure 3 is very similar to the configuration of Figure 2, but with the difference that the sensing arrangement is a potentiometric sensing arrangement, and in particular a potentiometric FET sensing arrangement, that measures the voltage value of the sensors $9_1, 9_2, 9_3$. The readout synapses in this configuration comprise an amplifier 27 and a filter element 25. In this configuration, the biasing circuit biases the sensors $9_1, 9_2, 9_3$ by setting the voltage for a reference electrode 23 that is immersed in the liquid to be sensed, the drain-to-source voltage V_{DS} , and/or the biasing current I_B . The sensor output signal is the source voltage level V_S at the source node S, and the sensor output current

is negligible. The outputs of the readout input synapses are connected to the readout neurons 15.

[0029] The configuration of Figure 4 is also very similar to the configuration of Figure 2, but with the difference that the respective sensing arrangement uses a three-electrode amperometric sensing arrangement. Thus, in this example, the respective sensors comprise three electrodes, namely a working electrode W, a reference electrode R, and a counter electrode C. V_R denotes the voltage of the reference electrode R, V_{WR} denotes the voltage between the working electrode W and the reference electrode R, while I_W denotes the current flowing through the working electrode. In this configuration, the biasing circuit biases the sensors $9_1, 9_2, 9_3$ by setting V_R and V_{WR} to govern the current flowing through the working electrode I_W , which is the sensor output signal. I_w is generated from an oxidising or reducing (redox) faradaic process taking place at the sensing surface of the W electrode, which depends upon the concentration of the analytes in the solution and the sensitivity S_i to each analyte. The outputs of the readout input synapses are connected to the readout neurons 15.

[0030] The configuration of Figure 5, on the other hand, is also very similar to the configuration of Figure 4, but with the difference that the respective sensing arrangement uses a two-electrode potentiometric sensing arrangement. Thus, in this example the respective sensors comprise only two electrodes, namely a working electrode W, and a reference electrode R. In this configuration, the biasing circuit biases the sensors $9_1, 9_2, 9_3$ by setting V_R . The sensor output signal is V_{WR} , a potential generated between the sensing surface of the electrode W in the solution and the reference electrode R. The potential depends upon the concentration of the analytes in the solution and the sensitivity S_i to each analyte. The readout circuit presents very high input impedance (i.e. negligible I_W) to ensure changes in this signal can be attributed to analyte interactions at the electrode W - solution interface. The outputs of the readout input synapses are here again connected to the readout neurons 15.

[0031] Figures 6 and 7 show two possible configurations or setups of the invention. In these specific examples, the sensed solution comprises hydrogen ions H^+ , sodium ions Na^+ , and potassium ions K^+ , which are examples of the properties used to predict the properties of interest of the substance, i.e. the sensed solution. In Figures 6 and 7, the values of the properties to be sensed are illustrated with white circles with a black outline. In other words, the white circles with a black outline describe the values of the multi-property inputs of the readout input synapses in one particular sensor or moment in time, and can be more broadly denoted by $x(t)$. Thus, the rectangles around these white circles with black outlines refer to the property the sensors are selective to. In this example, the predicted property is pH, i.e. the decimal logarithm of the reciprocal of the hydrogen ion activity, which is also responsible for the acidic or basic nature of the sensed solution. More broadly, in Figures 6 and 7, the

value of the predicted property of the sensed solution at any given moment in time is given by $\hat{y}(t)$. In both setups of Figures 6 and 7, the readout input synapses 13 translate input properties (e.g. ions) into input signals of readout neurons 15 of a domain processable by such neurons as described above. As shown, at least some of the readout neurons 15 are interconnected by readout recurrent synapses 17. The resulting output representations of this ANN pre-processor are fed forward to an ANN processor 7, which in the setup of Figure 6 comprises a feedforward neural network, and which in the setup of Figure 7 comprises a recurrent neural network. The feedforward neural network in the specific case of Figure 6 is a multi-layer perceptron, but the feedforward neural network could instead be any other feedforward network type, such as a (causal/dilated) convolutional neural network. In Figures 6 and 7, ANN neurons 15, 31, 37 are represented by black circles, while ANN synapses interconnecting the ANN neurons are represented with arrowed lines. In the setup of Figure 6, the ANN processor synapses are ANN processor feedforward synapses 33, while in the setup of Figure 7, the ANN processor synapses are ANN processor recurrent synapses 35 apart from the ANN processor feedforward synapses 33 connecting the ANN pre-processor or readout neurons 15 to the ANN processor neurons, and the ANN processor feedforward synapses 33 connecting the ANN processor neurons to an ANN processor output neuron 37, which is configured to output the value of the predicted property $\hat{y}(t)$.

[0032] Like the ANN pre-processor, the ANN processor feedforward synapses 33 and the ANN processor recurrent synapses 35 comprise one or more integrator compartments, which each are composed of an integrator filter element 25 with gain A 27, and optionally also summation elements 29. The ANN processor neurons 31, 37 also comprise one or more integrator compartments, which each are composed of a summation element 29 to sum up the neural input signals and/or neuron biases, an integrator filter element 25 with gain A 27, and optionally also of a spike generator 19 and/or additional summation elements 29. In the present embodiments, the compartment of the ANN processor neurons 31, 37 always includes a summation element 29 to sum up the neural input signals.

[0033] The artificial neural network processor 7 may thus be one of the following networks: a multi-layer perceptron, a convolutional neural network, a causal convolutional neural network, a dilated convolutional neural network, a recurrent neural network, or a combination of a convolutional neural network and a recurrent neural network. The output of at least one layer of the artificial neural network processor 7 may skip one or more following layers in the artificial neural network processor 7, and the output may be directly connected to the input of at least another succeeding layer of the artificial neural network processor 7 using skip feedforward connections or synapses. The readout circuit 5, on the other hand, may

be understood as an artificial neural network layer according to any one of the following networks: a multi-layer perceptron, a convolutional neural network, a causal convolutional neural network, a dilated convolutional neural network, or a recurrent neural network.

[0034] The process of operating the neurocomputational electrochemical sensing device is next explained with reference to the flow chart of Figure 8. In step 101, one or more properties to predict, such as the pH, of the substance are selected. This selection can be made for example by the operator of the device. In step 103, the sensors are selected that should sense the substance in the subsequent steps. This selection can be made by the operator, or the device can automatically select the sensors based on the knowledge of the properties to be predicted. The sensors are amperometric sensing electrodes, potentiometric sensing electrodes, amperometric sensing field-effect transistors, potentiometric sensing field-effect transistors, or any combination thereof. It is thus possible that not all of the output signals of the sensors of the sensor array are used to predict the output signals $\hat{y}(t)$. In step 105, the device parameters are initialised to e.g. the parameter values learned offline. More specifically, the parameters of the ANN processor 7 and the ANN pre-processor 11 are initialised. These parameters may be any of the following parameters: filter parameters, amplifier parameters, and the transconductance g_m . In step 107, the substance is contacted by the sensors. In step 109, the one or more properties of the substance are predicted. In step 111, it is determined whether or not a given loss, such as a (root) mean squared error prediction loss, is below a given threshold value ϵ . If this is the case, then the process may be terminated, or at least the loss determination may be terminated. If on the other hand, in step 111 it was determined that the loss is not below the threshold value, then in step 113, online learning of the ANN processor and/or the ANN pre-processor is conducted in order to compensate for sensor drift and/or cross-sensitivities. It is to be noted that steps 111 and 113 may at least partially be carried out parallel with step 109, i.e. substantially at the same time as step 109.

[0035] The proposed device is particularly advantageous to correct sensor non-idealities and to predict (bio)chemical properties of a substance using multimodal raw measurements collected continuously from a sensor array with sensors selective to properties correlated with target properties to predict as per resemblance of the teaching signals $y(t)$, and with sensors sensitive primarily to the main interfering analytes. The teaching signals $y(t)$ can be used to calculate a prediction loss jointly with the predicted ANN processor output signals $\hat{y}(t)$. From a prediction loss including a prediction error term depending on a difference between the teaching signals $y(t)$ and the predicted ANN processor output signals $\hat{y}(t)$, error back-propagation could be approximated by including both feedforward and feedback synapses. Such synapses would allow information about the prediction errors made

by the network to propagate through the network in the form of the error signals. Drift and matrix effects severely impair both performance and lifetime of electrochemical sensors such as FETs, but according to the present invention, an artificial neural network can be embedded in the device to cross-compensate such effects by fusing interrelated readout data from multiple sensors.

[0036] The proposed device may serve as a portable, self-calibrated electrochemical monitor to provide cost-effective and reliable assessment of analytes detectable by FET-based sensors and/or microelectrode sensors, for instance. In some embodiments, the device comprises an array of FET sensors with electrolyte-gate interfaces functionalised to be selective to properties correlated with the analytes of interest, or sensitive primarily to the main interferents of the measurements. All sensors are inherently sensitive to temperature due to the joint electrochemical and solid-state nature of these devices. The sensor array is coupled to an ANN trainable with sensor readings collected in the field to model both the temporal characteristics of sensor responses and the underlying relationships between sensor input data to predict analyte concentrations while compensating for sensor drift and matrix effects. The artificial neural network processor synapses 33, 35 and/or the artificial neural network pre-processor synapses 13, 17 form a first-type dynamical part, and the artificial neural network processor neurons 31, 37 and/or the artificial neural network pre-processor neurons 15 form a different, second-type dynamical part. Instances of the first-type dynamical part are configured as single-input, single-output synapses, and instances of the second-type dynamical part are configured as multiple-input, single-output neurons. The artificial neural network processor synapses 33, 35 and/or the artificial neural network pre-processor synapses 13, 17 and/or the artificial neural network processor neurons 31, 37 and/or the artificial neural network pre-processor neurons 15 comprise one or more integrator compartments, the synapses and the neurons forming a directed neural network exhibiting continuous-time dynamical behaviour.

[0037] While the invention has been illustrated and described in detail in the drawings and foregoing description, such illustration and description are to be considered illustrative or exemplary and not restrictive, the invention being not limited to the disclosed embodiments. Other embodiments and variants are understood, and can be achieved by those skilled in the art when carrying out the claimed invention, based on a study of the drawings, the disclosure and the appended claims. Further variants of the invention may be obtained by combining any of the above teachings.

[0038] In the claims, the word "comprising" does not exclude other elements or steps, and the indefinite article "a" or "an" does not exclude a plurality. The mere fact that different features are recited in mutually different dependent claims does not indicate that a combination of these features cannot be advantageously used. Any ref-

erence signs in the claims should not be construed as limiting the scope of the invention.

5 Claims

1. A neurocomputational electrochemical sensing device (1) for predicting properties of a substance, the device (1) comprising:

- a plurality of electrochemical sensors ($9_1, 9_2, 9_3$) constituting a sensor array (3), a respective electrochemical sensor being sensitive to sensed attributes advantageous to predict a set of properties of interest of the substance, the respective electrochemical sensor being configured to output a sensor output signal indicative of a sensor response of the respective electrochemical sensor ($9_1, 9_2, 9_3$) to measurable changes in the sensed attributes of the substance;
- a readout circuit (5) for biasing the sensors ($9_1, 9_2, 9_3$) and for conditioning the sensor output signals into readout circuit output signals to facilitate further processing of the sensor responses; and
- an artificial neural network processor (7) for processing the readout circuit output signals, the artificial neural network processor (7) comprising artificial neural network processor neurons (31, 37) interconnected by artificial neural network processor synapses (33, 35), the artificial neural network processor (7) being configured to output a set of artificial neural network processor output signals $\hat{y}(t)$ whose signal values are indicative of the properties to predict,

wherein the electrochemical sensors ($9_1, 9_2, 9_3$) of the sensor array (3) comprise a first set of first electrochemical sensors selective to properties correlated with the desired properties to predict, and a second set of second electrochemical sensors sensitive primarily to one or more main interferents of the substance, and wherein at least the artificial neural network processor neurons (31, 37) and/or the artificial neural network processor synapses (33, 35) are configured to be trained to compensate for sensor drift and/or sensor cross-sensitivities upon generating the artificial neural network processor output signals $\hat{y}(t)$.

2. The neurocomputational electrochemical sensing device (1) according to claim 1, wherein one or more of the readout circuit (5), the artificial neural network processor (7), and the electrochemical sensors ($9_1, 9_2, 9_3$) of the sensor array (3) are integrated in a common substrate.

3. The neurocomputational electrochemical sensing device (1) according to claim 2, wherein the substrate is embedded into a common carrier integrating miniaturised structures of fluid manipulation and/or control suitable for wafer-level production. 5
4. The neurocomputational electrochemical sensing device (1) according to any one of the preceding claims, wherein the electrochemical sensors (9_1 , 9_2 , 9_3) are amperometric sensing electrodes, potentiometric sensing electrodes, amperometric sensing field-effect transistors, potentiometric sensing field-effect transistors, or any combination thereof. 10
5. The neurocomputational electrochemical sensing device (1) according to any of the preceding claims, wherein the readout circuit (5) and the electrochemical sensors (9_1 , 9_2 , 9_3) collectively constitute an artificial neural network pre-processor (11) comprising artificial neural network pre-processor synapses (13, 17) and artificial neural network pre-processor neurons (15), the artificial neural network pre-processor synapses (13, 17) comprising readout input synapses (13) configured to feed the sensor output signals as processed to the artificial neural network pre-processor neurons (15), and readout recurrent synapses (17) interconnecting at least some of the artificial neural network pre-processor neurons (15). 15
6. The neurocomputational electrochemical sensing device (1) according to claim 5, wherein the artificial neural network pre-processor synapses (13, 17) and/or the artificial neural network pre-processor neurons (15) are configured to decompose the sensor output signals into informative, discriminating and/or independent properties or characteristics of the substance to facilitate modelling dependencies between any combination of sensible (bio)chemical properties and/or teaching signals $y(t)$ representing the signals to predict by the artificial neural network processor (7). 20
7. The neurocomputational electrochemical sensing device (1) according to any one of the preceding claims, wherein the artificial neural network processor synapses (33, 35) and/or the artificial neural network pre-processor synapses (13, 17) form a first-type dynamical part, and the artificial neural network processor neurons (31, 37) and/or the artificial neural network pre-processor neurons (15) form a different, second-type dynamical part, instances of the first-type dynamical part being configured as single-input, single-output synapses, and instances of the second-type dynamical part being configured as multiple-input, single-output neurons, and wherein the artificial neural network processor synapses (33, 35) and/or the artificial neural network pre-processor synapses (13, 17) and/or the artificial neural network processor neurons (31, 37) and/or the artificial neural network pre-processor neurons (15) comprise one or more integrator compartments, the artificial neural network processor synapses (33, 35), the artificial neural network pre-processor synapses (13, 17), the artificial neural network processor neurons (31, 37), and the artificial neural network pre-processor neurons (15) forming a directed neural network exhibiting continuous-time dynamical behaviour. 25
8. The neurocomputational electrochemical sensing device (1) according to any one of the preceding claims, wherein the artificial neural network processor neurons (31, 37) and/or the artificial neural network pre-processor neurons (15), and/or the artificial neural network processor synapses (33, 35) and/or the artificial neural network pre-processor synapses (13, 17), are configured to be trained on a dataset collected offline by using a backpropagation optimisation method to minimise a Kullback-Leibler divergence loss function, or a simplified functional equivalent function, with respect to parameters of the neurocomputational electrochemical sensing device (1). 30
9. The neurocomputational electrochemical sensing device (1) according to any one of the preceding claims, wherein the artificial neural network processor synapses (33, 35) and/or the artificial neural network pre-processor synapses (13, 17), and/or the artificial neural network processor neurons (31, 37) and/or the artificial neural network pre-processor neurons (15) are configured to be fine-trained online by using plasticity rules which only employ signals locally available in space and time in the respective neurons (15, 31, 37) and synapses (13, 17, 33, 35) of the artificial neural network processor (7) and/or the artificial neural network pre-processor (11), and that are propagated by feedforward and feedback synapses. 35
10. The neurocomputational electrochemical sensing device (1) according to any one of the preceding claims wherein, upon generating the artificial neural network processor output signals $\hat{y}(t)$, the sensor drift is configured to be compensated by modelling temporal evolution of the teaching signals $y(t)$ with respect to the sensor output signals subject to temporal drift, the teaching signals $y(t)$ representing the signals to predict by the artificial neural network processor (7), and wherein the cross-sensitivities are configured to be compensated by modelling underlying temporal relationships between (i) sensor output signals selective to the properties correlated with the desired properties to predict, (ii) sensor output signals sensitive primarily to the one or more main interferents, and/or (iii) the teaching signals $y(t)$. 40
11. The neurocomputational electrochemical sensing 45

device (1) according to any one of the preceding claims, wherein the artificial neural network processor (7) is one of the following networks: a multi-layer perceptron, a convolutional neural network, a causal convolutional neural network, a dilated convolutional neural network, a recurrent neural network, or a combination of a convolutional neural network and a recurrent neural network. 5

12. The neurocomputational electrochemical sensing device (1) according to any one of the preceding claims, wherein an output of at least one layer of the artificial neural network processor (7) skips one or more following layers in the artificial neural network processor (7), and the output is directly connected to an input of at least another succeeding layer of the artificial neural network processor (7) using skip connections. 10 15

13. The neurocomputational electrochemical sensing device (1) according to any one of the preceding claims, wherein the readout circuit (5) is an artificial neural network layer according to any one of the following networks: a multi-layer perceptron, a convolutional neural network, a causal convolutional neural network, a dilated convolutional neural network, or a recurrent neural network. 20 25

14. A method of predicting properties of a substance by using the neurocomputational electrochemical sensing device (1) according to any one of the preceding claims, the method comprising: 30

- selecting (101) properties of the substance to predict; 35
- contacting (107) the electrochemical sensors (9₁, 9₂, 9₃) with the substance;
- predicting (109) the properties of the substance; and
- carrying out (113) an online learning process in order to train at least the artificial neural network processor neurons (31, 37) and/or the artificial neural network processor synapses (33, 35) to compensate for sensor drift and/or cross-sensitivities upon generating the artificial neural network processor output signals $\hat{y}(t)$. 40 45

15. The method according to claim 14, wherein the method further comprises determining (111) whether or not a given loss is below a given threshold value, and carrying out the online learning process only if the loss is not below the given threshold value. 50

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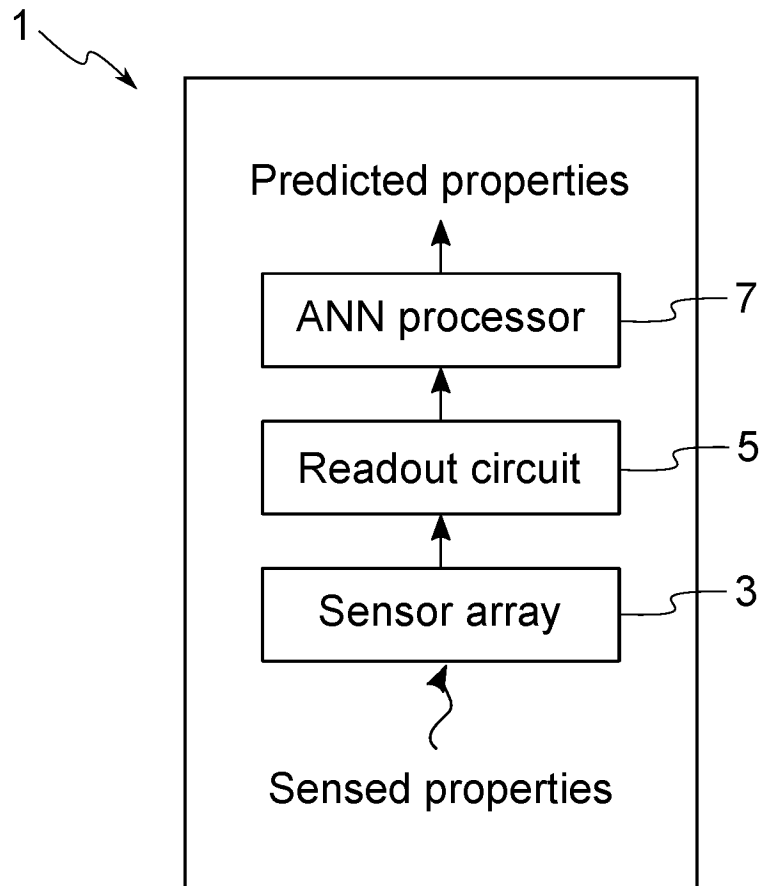


Fig. 1

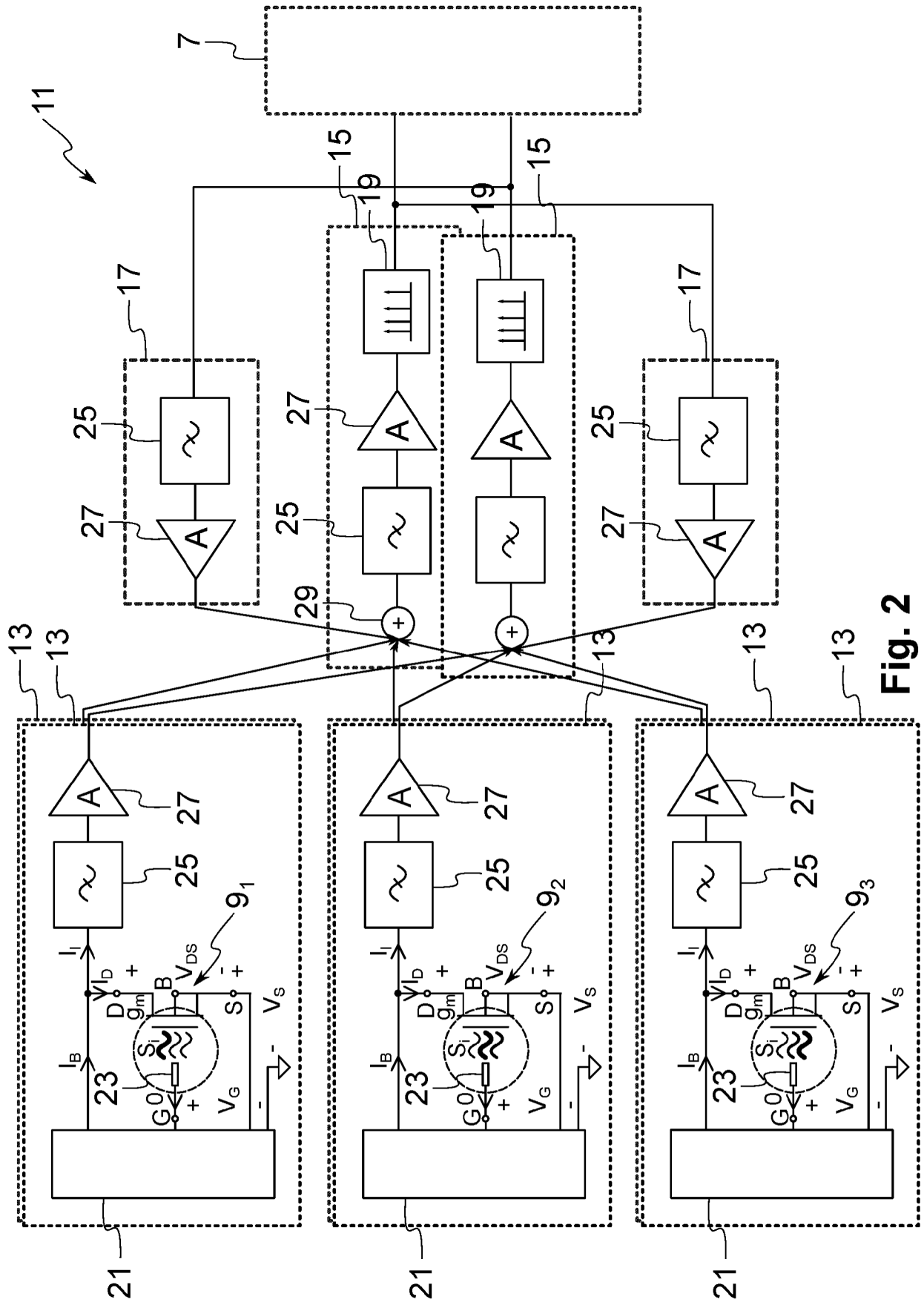


Fig. 2

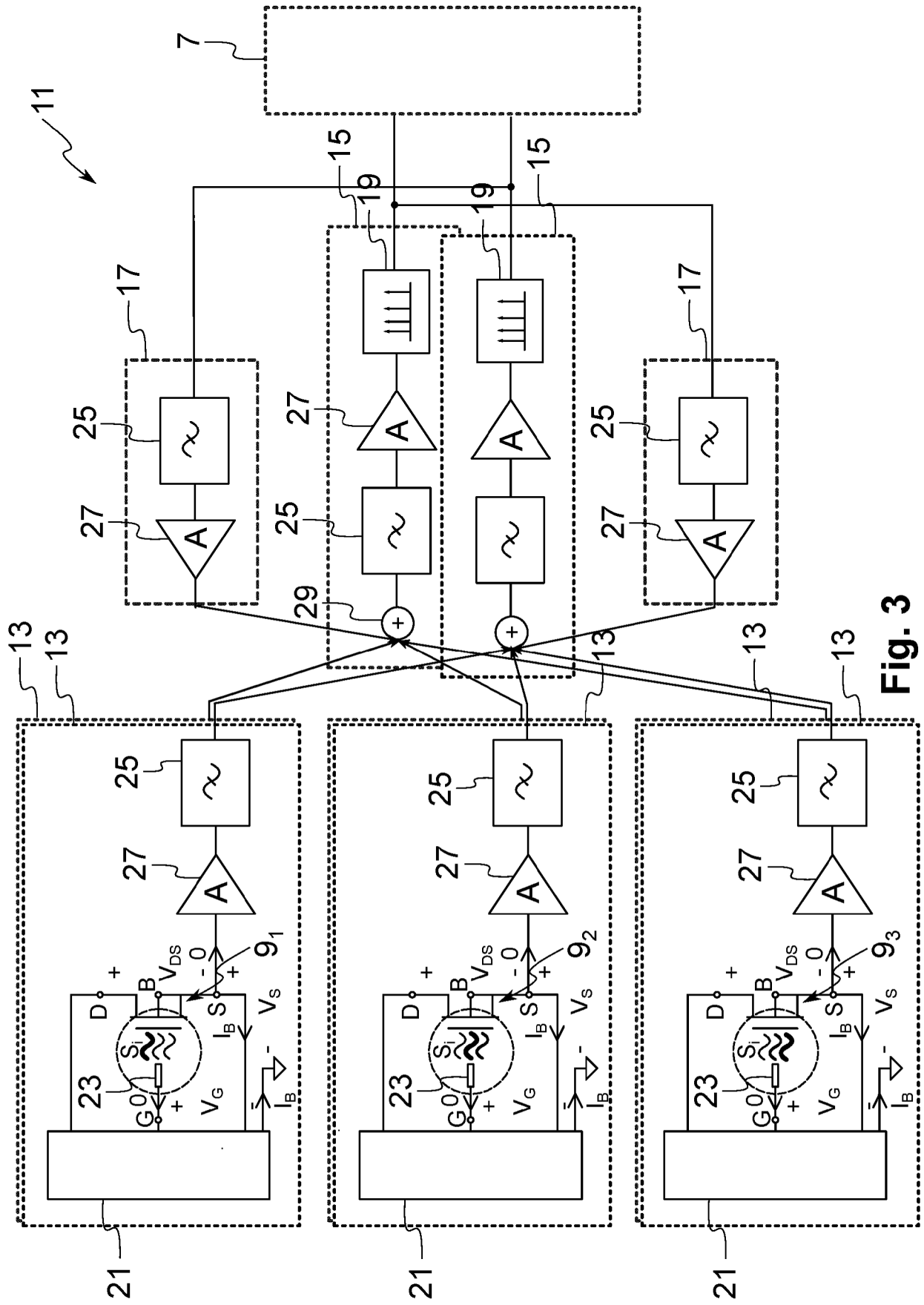


Fig. 3

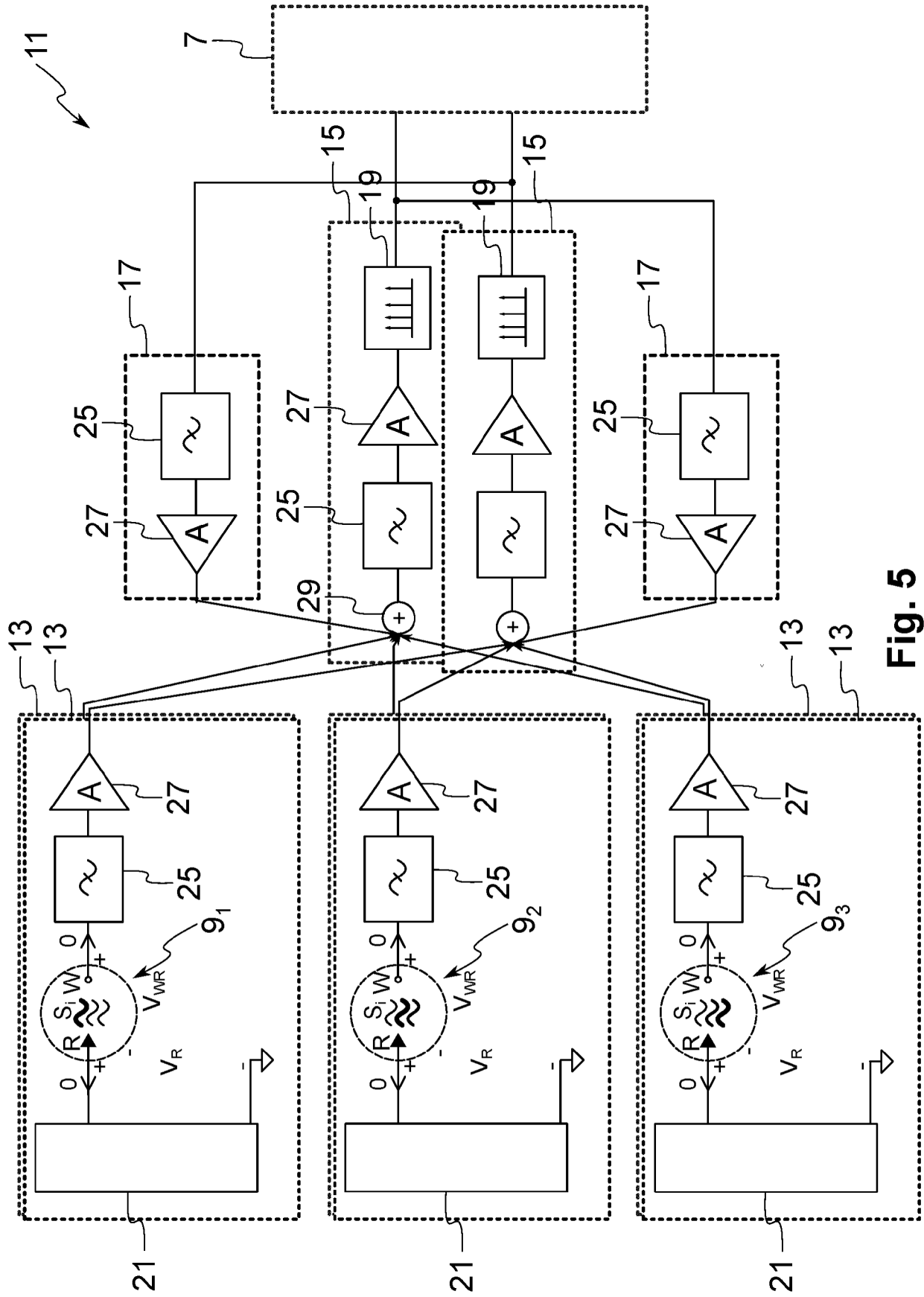


Fig. 5

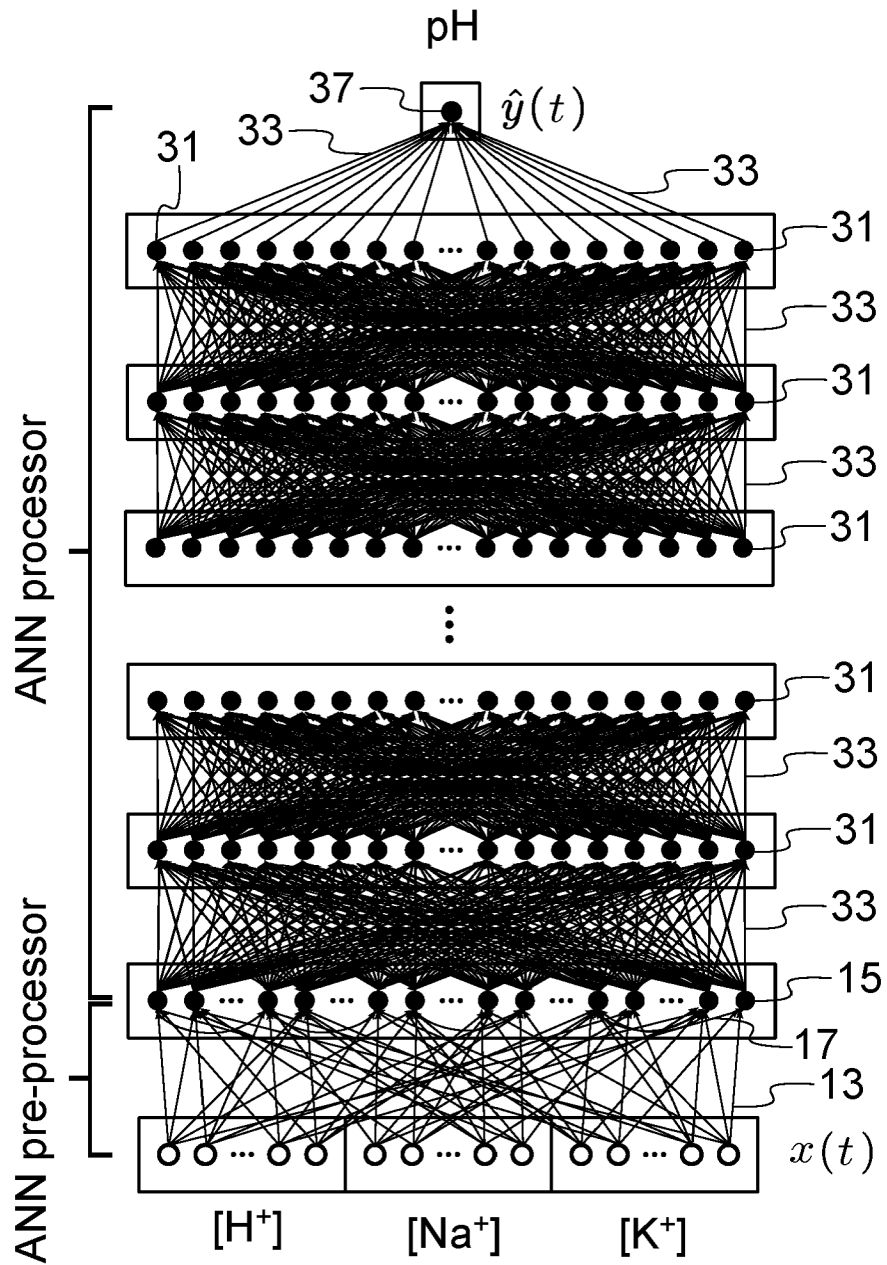


Fig. 6

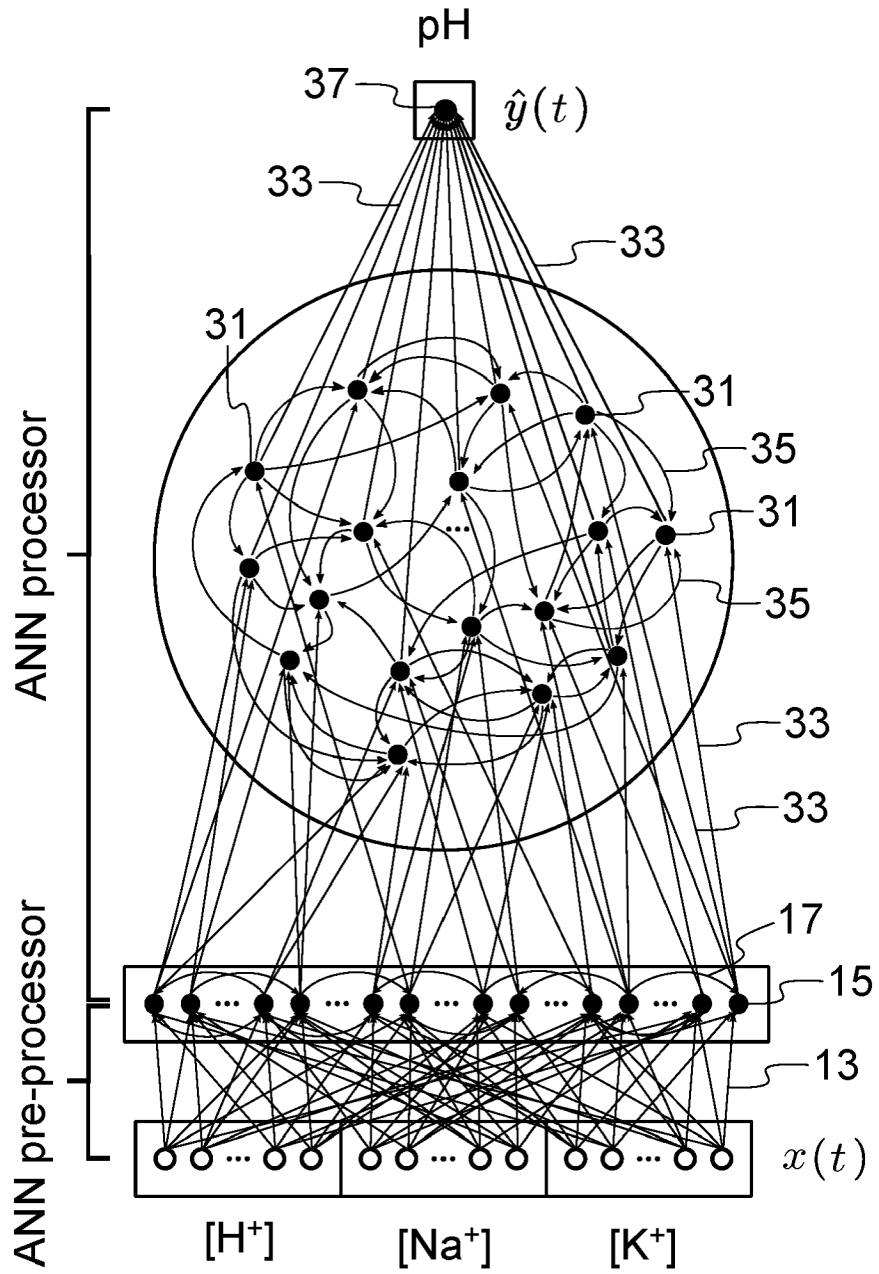
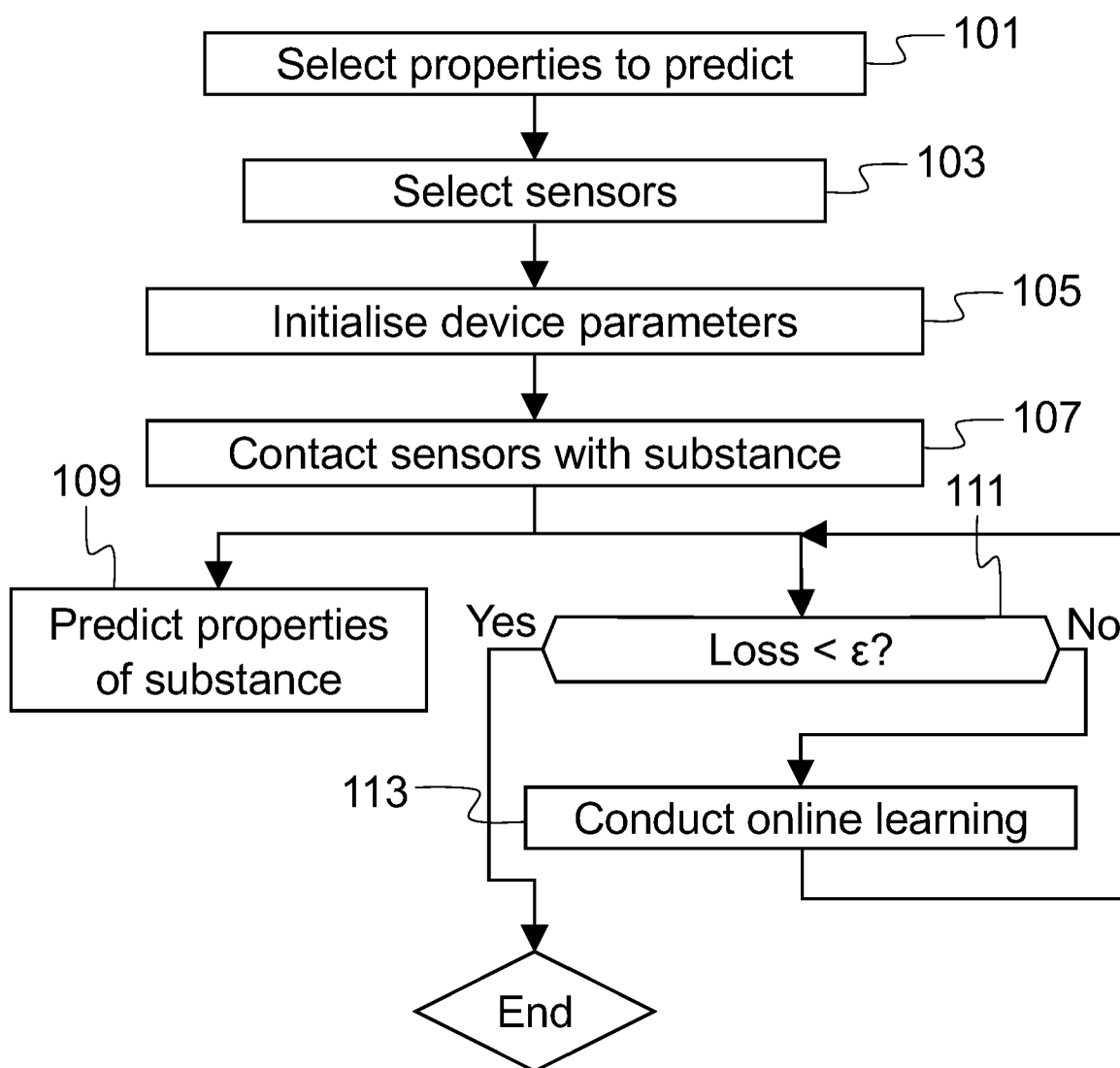


Fig. 7

**Fig. 8**



EUROPEAN SEARCH REPORT

Application Number
EP 21 18 8804

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X	MASCHENKO A.A. ET AL: "On the feasibility to apply a neural network processor for analyzing a gas response of a multisensor microarray", SENSORS AND ACTUATORS A: PHYSICAL, vol. 190, 1 February 2013 (2013-02-01), pages 61-65, XP055878544, NL ISSN: 0924-4247, DOI: 10.1016/j.sna.2012.11.016 * the whole document * -----	1-15	
E	EP 3 862 930 A1 (UNIV ZUERICH [CH]; CONSEJO SUPERIOR INVESTIGACION [ES]) 11 August 2021 (2021-08-11) * the whole document * -----	1-15	TECHNICAL FIELDS SEARCHED (IPC) G01N
2 The present search report has been drawn up for all claims			
Place of search Munich		Date of completion of the search 17 January 2022	Examiner De Masi, Rita
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5 This annex lists the patent family members relating to the patent documents cited in the above-mentioned European search report.
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17-01-2022

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