

AN AI SENSING DEVICE FOR A BROAD SPECTRUM OF GAS AND VAPOR DETECTION

TECHNICAL FIELD

[0001] This invention relates broadly to a computerized method and a sensor device for determining respective presence and concentrations of multiple gases and/or volatile organic compounds, and to a method of training the sensor device.

BACKGROUND

[0002] Any mention and/or discussion of prior art throughout the specification should not be considered, in any way, as an admission that this prior art is well known or forms part of common general knowledge in the field.

[0003] There are numerous literatures on the use of machine learning technique, also referred to as artificial intelligence (AI), on gas and vapor sensing devices, which are sometimes referred to as modern electronic nose (eNose). For example, the article, Towards a Chemiresistive Sensor-Integrated Electronic Nose: A Review, found on doi.org/10.3390/s131014214, provides a list of all commercially available eNose devices found in 2013.

[0004] Existing studies/devices use either highly selective materials that will only respond to a specific type of gases/volatile organic compounds (VOCs), or perform chemical modifications. This increases the complexity and cost of such sensors.

[0005] Also, in existing studies/products, chemical fingerprints of each gas or VOC are derived from a unique arrayed pattern formed by a combination of electrical responses acquired from individual sensing elements, each crafted differently in sensitivity, cross sensitivity and specificity, in a sensor array when it is exposed to an analyte. For example, a chemical fingerprint can be a unique combinatorial variation in the mean current from an array of 9 sensors which are arranged in a 3-by-3 row and column format, whereby the 3 cells at the top right corner would always be higher than the lower 3 cells in the bottom left corner when exposed to a particular type of analyte and not others. This also increases the complexity and cost of such sensors.

[0006] While the method disclosed in [“Selective Gas Sensing with a Single Pristine Graphene Transistor, Sergey Rumyantsev, Guanxiong Liu, Michael S. Shur, Radislav A. Potyrailo and Alexander A. Balandin”, Nano Lett. 2012, 12, 5, 2294-2298 Publication Date:

April 16, 2012] would enable one to use a single 2DM based chemiresistor for measuring multiple sources of gas/vapour, it cannot be used when more than one gas/VOCs types are present in the same environment at the same time (i.e. simultaneous variations of more than one gas/vapour type). This is because multiple characteristic Lorentzian frequencies representing each of the specific gas/vapour type would be generated in this case and the user would not be able to locate them all from the FFT spectrum analyzer used in that work, since, as defined by the authors of the work, the characteristic Lorentzian frequency is the frequency with the highest power spectral density found in the plot of noise spectral density multiplied by frequency vs frequency (i.e. Lorentzian noise spectral). Thus, only one characteristic frequency would be extracted from this multiple gas/VOCs measurement and the user (human) could not decipher the rest of the information still hidden in the data collected.

[0007] Moreover, the method disclosed in the abovementioned paper still relies on the overall incremental change in the conductivity of the chemiresistor when it is under exposure from multiple gases/VOCs in the environment for the measurement of the concentration level. therefore, one would also not be able to tell what percentage of changes each individual gas/VOCs has contributed to the overall incremental change detected in the conductivity of the chemiresistor.

[0008] Additionally, the input features used for machine learning in existing studies/devices contain individual electrical responses from respective multiple sensors placed in proximity and exposed to the same analyte. This increases the complexity of such sensors.

[0009] Embodiments of the present invention seek to address one or more of the above-mentioned needs.

SUMMARY

[0010] In accordance with a first aspect of the present invention there is provided a computerized method of determining respective presence and concentrations of multiple gases and/or volatile organic compounds, the method comprising the steps of exposing one or more sensing elements with the same chemical and physical properties to the multiple gases and/or volatile organic compounds; measuring electrical time series data of the one or more sensing elements during the exposure; analyzing the electrical time series data and Lorentzian noise information of the electrical time series data by an Artificial Intelligence (AI) system; and determining the respective presence and concentrations of the multiple gases and/or volatile organic compounds based on the analysis of the electrical time series data and the Lorentzian noise information of the electrical time series data.

[0011] In accordance with a second aspect of the present invention there is provided a sensor device capable of determining respective presence and concentrations of multiple gases and/or volatile organic compounds, the sensor device comprising one or more sensing elements made from a substantially identical sensing material; and an Artificial Intelligence (AI) system; wherein the AI system is configured to analyze electrical time series data of the one or more sensing elements and Lorentzian noise information of the electrical time series data to determine the respective presence and/or concentrations of multiple gases and/or volatile organic compounds based on the analysis of the electrical time series data and the Lorentzian noise information of the electrical time series data.

[0012] In accordance with a third aspect of the present invention there is provided a method of training a sensor device of the second aspect to be capable of determining respective presence and/or concentrations of multiple gases and/or volatile organic compounds.

BRIEF DESCRIPTION OF THE DRAWINGS

[0013] The invention will be better understood with reference to the detailed description when considered in conjunction with the non-limiting examples and the accompanying drawings, in which:

[0014] Fig. 1 shows diagrams illustrating the fabrication process of black phosphorus (bP), which is a two-dimensional material (2DM), chemiresistor, according to an example embodiment.

[0015] Fig. 2 shows the output characteristic (drain current, I_D , vs drain voltage, V_D) of the chemiresistor, according to an example embodiment.

[0016] Fig. 3 shows the experimental setup of a wireless all-in-one gas sensor node 300 according to an example embodiment for relative humidity (RH) measurement, according to an example embodiment.

[0017] Fig. 4 shows a block diagram of a sensor node according to an example embodiment.

[0018] Fig. 5 shows a flow diagram illustrating the data collection process according to a preferred embodiment in training a single 2DM-based chemiresistor to classify and quantify multiple species of gases/vapours that are present in the same environment.

[0019] Fig. 6 shows the statistical information (i.e. mean, median, and standard deviation) of 68 samples collected for the first 4 days, according to an example embodiment.

[0020] Fig. 7 shows variations in the measured current at similar RH, according to an example embodiment.

[0021] Fig. 8 shows the experimental setup for the training and testing of an all-in-one gas sensor according to an example embodiment for CO₂, N₂O, and RH.

[0022] Fig. 9 shows the experimental setup for the training and testing of an all-in-one gas sensor according to an example embodiment for no plant, plant without VOC emission, and plant with VOCs submission.

[0023] Fig. 10 illustrates the process of training a single 2DM-based chemiresistor via machine learning (ML) for classifying and quantifying multiple sources of gases/VOCs that are present simultaneously in the same environment, according to an example embodiment.

[0024] Fig. 11 shows the signal flow diagram illustrating prediction for Multi-gas/VOCs sensing according to an example embodiment.

[0025] Fig. 12 describes briefly the system implementation block-diagram of an all-in-one gas sensor according to an example embodiment as an air quality sensor in a standalone consumer product for tracking health or as a climate monitoring sensing node in a wireless sensor network for production control in a factory or industrial safety application.

[0026] Fig. 13 shows the characteristic Lorentzian frequencies extracted from 3 different ambient environments and can be seen as the first proof of principle for using characteristic Lorentzian frequencies to distinguish multiple gases from a single 2DM-based chemiresistor according to an example embodiment.

[0027] Fig. 14 shows the characteristic Lorentzian frequencies extracted from 3 other different ambient environments of another ambient type-0, where there is no plant in the enclosure, another ambient type-1 where there is a plant that is known to not emit any VOCs in the enclosure, and finally another ambient type-2 where there is a plant that is known to emit strong VOCs in the enclosure, according to an example embodiment.

[0028] Fig. 15 shows the prediction accuracy of an all-in-one sensor according to an example embodiment for RH.

[0029] Fig. 16 shows the prediction accuracy of an all-in-one sensor according to an example embodiment for CO₂ gas.

[0030] Fig. 17 shows the prediction accuracy of an all-in-one sensor according to an example embodiment for N₂O gas.

[0031] Fig. 18 summarizes the classification and regression results achieved from two different 2DM-based sensors according to example embodiments.

[0032] Figure 19 shows a flow chart illustrating a computerized method of determining respective presence and concentrations of multiple gases and/or volatile organic compounds, according to an example embodiment.

[0033] Figure 20 shows a schematic diagram illustrating a sensor device capable of determining respective presence and concentrations of multiple gases and/or volatile organic compounds, according to an example embodiment.

DETAILED DESCRIPTION

[0034] Embodiments of the present invention provide an all-in-one smart sensor device that can simultaneously detect the presence and quantify the concentration of multiple types of gases and VOCs wirelessly using only a single physical sensor, or an array of sensors with the same chemical and physical properties. The all-in-one sensor device uses two-dimensional layered materials that are highly sensitive to a broad variety of gases/VOCs and functionalizes its selectivity to different gases or VOCs through respective AI models (i.e. AI Engines), developed by exhaustive machine-learning (ML) in real environment settings. By having software control over the selectivity of the sensor device according to example embodiments, new sensing capabilities can be added on demand in real-time without any change in the physical hardware, which is not currently available in any conventional sensor system.

[0035] In general, the wireless all-in-one sensor smart sensor according to example embodiments can be used on an Internet of Thing (IoT) platform in tracking the quality of health, product, and produce. Embodiments of the present invention have wide applications in environmental monitoring and emission control, personal and military safety, production control in agriculture, manufacturing and medical diagnostics. Embodiments of the present invention can also be adopted for heating, ventilation, and air conditioning, e.g heating, ventilation, and air conditioning (HVAC), to reduce energy consumption by better control of the air conditioning.

[0036] The sensing material used according to example embodiments include two-dimensional layered inorganic materials (2DMs) that are highly sensitive to a broad variety of gases and VOCs (i.e. non-selective) by physical nature, while existing studies/devices use either highly selective materials that will only respond to a particular type of gases/VOCs, or perform chemical modifications or functionalization to the sensing material to create specificity to a particular analyte.

[0037] Selectivity according to example embodiments: Discrimination of gas/VOCs type is achieved using machine learning (ML) techniques instead of chemically or physically functionalizing the sensing material as in existing studies/devices.

[0038] Chemical fingerprints of various gases or VOCs according to example embodiment are derived from unique patterns detected using a machine learning algorithm on information

gathered from the low-frequency noise spectra of a single chemiresistor type via ML training and deployment methodology.

[0039] Embodiments of the present invention advantageously extract information not previously accessible from the FFT spectrum analyzer used in existing studies/devices via ML training and deployment methodology.

[0040] Embodiments of the present invention use Lorentzian frequencies that relate to the kinetics of the adsorption and desorption of the molecules as a result of vapor exposure, which corresponds to a much lower characteristic frequencies compared to the Lorentzian frequencies that relate to the charge traps created as a result of vapor exposure as in existing studies/devices.

[0041] The input features used for machine learning according to example embodiments do not contain individual electrical responses from respective multiple sensors placed in proximity and exposed to the same analyte. Instead, the input features used according to example embodiments contain information such as:

- the time dependent electrical responses (i.e. channel resistance) from a single type of 2DM-based chemiresistor,
- its derivatives such as the characteristic Lorentzian frequencies (i.e. peaks with the maximum power spectral density) and their respective power spectral density from the plot of noise spectral density multiplied by frequency vs frequency (i.e. Lorentzian noise spectral).
- the characteristic Lorentzian desorption time (i.e. the inverse of the Lorentzian characteristic frequency),
- the Kurt, Skew, median of the Lorentzian noise spectral,
- the power spectral density ratio of the characteristic Lorentzian frequency to the median of the Lorentzian noise spectral,
- the numbers of Lorentzian Peaks found in the Lorentzian noise spectral, the median of these peaks and the frequencies associated to these peaks,
- the full width half maximum and full width full maximum of the characteristic Lorentzian peak (i.e. the peak with the highest power spectral density), and,
- the ambient temperature.

[0042] It is noted that other operating conditions such as run time may be used in different embodiments. Also, it is noted that the operating conditions such as the ambient temperature may not be used as input features in some example embodiments, e.g. where the sensor device is to be configured to only be used in certain operating conditions, such as at room temperature.

[0043] The general physical mechanism of selective gas sensing using just a single 2D material as a chemiresistor according to example embodiments is based on the recognition

resulting from systematic study that some gases change the electrical resistance of 2DM, e.g. graphene, devices without changing their low-frequency noise spectra while other gases modify the noise spectra by inducing Lorentzian components with distinctive features [“Selective Gas Sensing with a Single Pristine Graphene Transistor, Sergey Rumyantsev, Guanxiong Liu, Michael S. Shur, Radislav A. Potyrailo and Alexander A. Balandin”, Nano Lett. 2012, 12, 5, 2294-2298 Publication Date: April 16, 2012]. According to that study, there are two reasons for the appearance of the Lorentzian noise in graphene under gas exposure. First, the gas molecules can create specific traps and scattering centers in graphene, which lead to either fluctuation in the number of carriers due to the fluctuations of traps occupancy or to the mobility fluctuations due to fluctuations of the scattering cross sections. Second, the kinetics of the adsorption and desorption of molecules from exposure would also contribute to noise. The characteristic time scale for the adsorption and desorption of vapours is reported to be in several hundreds of seconds. Although the method disclosed in that study would enable one to use a single chemiresistor for measuring multiple sources of gas/VOCs, it cannot be used for quantitative analysis when more than one gas/VOCs types are present in the same environment at the same time (e.g. simultaneous variations of N_2O , CO_2 and relative humidity in the same environment). E.g. if one introduces only ethanol into an environment, then by analysing the FFT spectrum and observing a Lorentzian frequency, f_c , at 399Hz, ethanol can be determined and the concentration of ethanol can be obtained by calculating dR/R (R =channel resistance measured from a multi-meter and dR is the change in magnitude before exposure and after exposure). However, if both ethanol and methanol are present in the environment, their respective concentration levels cannot be determined from the measured dR/R .

[0044] Embodiments of the present invention can instead advantageously provide a multi-gas/vapour sensor using a single sensing material configured to not only determine the types of gas/vapour species present but also their respective concentration levels.

[0045] **Fabrication of chemiresistor(s) for sensor devices according to example embodiments**

[0046] Fig. 1 shows diagrams illustrating the fabrication process of a black phosphorus (bP), which is a two-dimensional material (2DM), chemiresistor for sensing relative humidity, according to example embodiments. A photoresist layer 100 is deposited on a substrate, here a glass substrate 102, to provide patterns 104, 106 for two electrical terminals 108, 110, here Au/Ni (30 nm/1 nm), by using a standard lift-off process after metal 112 deposition. In this embodiment, an AJA ATC-2200 UHV Sputter was used for the metal 112 deposition and a

laser writer LW405B was used for patterning of the photoresist layer 100. After lift-off of the metal 112 leaving the terminals 108, 110 on the substrate 102, the electrical channel, here an exfoliated bP flake 114, of the chemiresistor 116 is then deposited across the two terminals 108, 110 by a dry transfer technique using polydimethylsiloxane (PDMS) in this example embodiment. The channel length and width of the chemiresistor is ~ 1 mm by 0.25 mm in a non-limiting example, and its Raman spectrum 118 shows the typical signature of a black phosphorus at 363 cm^{-1} , 440 cm^{-1} , and 467 cm^{-1} .

[0047] The output characteristic (drain current, I_D , vs drain voltage, V_D) of the chemiresistor 116 is shown in Fig. 2. As there is no noticeable hysteresis loop in the measured current in the double voltage sweep measurement, there are no significant number of hidden traps to impede the chemiresistor's 116 current flow, allowing the bP chemiresistor 116 according to example embodiments to operate in low voltage range. It is noted that for large scale operation, commercial printing process will preferably be used to prepare chemiresistors according to various example embodiments, instead of dry transfer technique using polydimethylsiloxane (PDMS).

[0048] **Functional description of the wireless sensor according to an example embodiment**

[0049] Fig. 3 shows the experimental setup of a wireless all-in-one gas sensor node 300 according to an example embodiment for relative humidity (RH) measurement. The sensor node 300 comprises has a Bluetooth enabled tablet 302 to wirelessly receive the measured voltage across the chemiresistor 304 from a Bluetooth low energy microcontroller unit (TI CC2541) on a PCB 305, in this example embodiment. The relative humidity is controlled by the desiccator 306 filled with silica gel and the reference RH sensor 308 provides the reference data used in the machine learning according to an example embodiment. The detailed functions circuitry on the PCB 305 which includes an analog front-end unit (AFE), analog-to-digital converter (ADC), the microcontroller unit (MCU), and battery booster (here TI TPS61220 & LM4120) will be described with reference to the block diagram shown in Fig. 4.

[0050] As can be seen from the diagram in Fig. 4, the chemiresistor 400 is connected across the control electrode (CE) and working electrode (WE) terminals of the AFE 402 (here TI LM91000). The bias voltage to the chemiresistor 400 is supplied by a 3 V coin-cell battery 404 (here CR-2032) and is preset to the lowest value of 25 mV. The battery booster unit 406 regulates this battery source and provides a stable reference voltage of 2.5 V to the control amplifier (A1) 407, the transimpedance amplifier (TIA) 409 and the analog-to-digital converter (ADC) found inside the micro controller unit and radio frequency system-on-chip (here MCU

+ RF SoC CC2541) 412. The reference electrode (RE) terminal of the AFE 402 is shorted to CE to ensure a constant 25 mV is held across CE and WE at all time. Under this configuration, the AFE 402 operates like a potentiostat and any changes in the resistance of the chemiresistor 400 will be reflected in the current flowing across the terminals 408, 410 and be transformed into a voltage by the TIA 409. The ADC in the MCU 412 will then convert this analog voltage into a digital signal and the Bluetooth transmitter 414 will transmit this digital information to the receiver (Bluetooth enabled Tablet 302, Fig. 3) periodically at a preset interval of e.g. 0.3 s (note: lowest preset interval available = 10 ms). When the digital voltage signal is received by the tablet 302 (Fig. 3), the digital voltage signal will be reinstated into its original analog current value by a software application in tablet 302 (Fig. 3) based on the settings in the ADC in the MCU 412 and TIA 409.

[0051] **Data Collection for Machine Learning according to example embodiments**

[0052] Fig. 5 shows a flow diagram illustrating the data collection process according to a preferred embodiment in training a single 2DM-based chemiresistor to classify and quantify multiple species of gases/vapours that are present in the same environment. Indicated as step 1, in an enclosed environment, expose a single 2DM-based chemiresistor to the desired number N and types of gases/VOCs in a controlled manner and decide which gases/VOCs to measure as well as the range of the concentration level to adjust. Indicated as step 2, systematically vary the concentration of one gas/VOC and measure the corresponding channel resistance of the chemiresistor. Collect a dataset of measurements at different concentration levels, preferably ensuring the measurement points are equally distributed in the decided adjustment range. This dataset is classified as ambient type 0 (increment this number by one for each new dataset for the respective different gases/VOCs).

[0053] Indicated as step 3a, repeat from step 1 and choose another gas/VOCs type until the concentration of all gases/VOCs have been varied.

[0054] Indicated as step 3b, repeat from step 1 and choose two gas/VOCs type for simultaneous variation of concentration until the concentration of all two-gas/VOCs-combinations have been varied.

[0055] Indicated as step 3c, repeat from step 1 and each time increase the number of gas/VOCs types that is simultaneously varied (i.e. three-gas/VOCs-combination, four-gas/VOCs-combinations etc.) until the concentration of all possible N-gas/VOCs-combinations have been varied. Data collection is then complete and machine training is started.

[0056] It is noted that in different embodiments the naming of the ambient type does not have to be based on how many parameters were varied during the training, as described above

with reference to Figure 5. For example, the naming of the ambient type may be based on when the training is carried out in a chronological manner. Generally, as long as all relevant combinations of gases have been tested and trained on the sensor according to example embodiments, the trained models are suitable for use according to various example embodiments.

[0057] **Data Collection for Machine Learning for N=3 [H₂O/RH, CO₂ and N₂O] according to an example embodiment**

[0058] **Ambient Type 0:** Variation in relative humidity, RH, and CO₂ only. The desiccator 306 shown in Fig. 3 is first filled with freshly baked silica gel under the perforated plate with the battery powered wireless bP sensor 304. The desiccator 306 is then closed to allow the silica gel to reduce the RH in the desiccator 306. Once the readings on reference RH sensor 308 become stable, data collection is started by allowing the current flowing across the bP chemiresistor 304 to be recorded wirelessly on tablet 300 at an interval of 0.3 s for 3 mins. Accordingly, in this non-limiting example, each sample reading of the RH value would consist of 600 data points representing the measured current flowing across the bP chemiresistor 304 during this 3 mins period. Datasets with any changes in the RH value within the 3 mins recording time would be discarded. The experiment is conducted across 5 months and the only time the environment of desiccator 306 is disrupted is to power on-and-off the wireless sensor (to conserve battery energy) at the start and end of each day. The number of sample files collected for RH is 945 (i.e. sample size = 945) with each sample containing 600 measurement points. The ambient concentration of N₂O is assumed to be not changing for this ambient type 0 but ambient CO₂ concentration in the desiccator is found to be decreasing via diffusion throughout all the experiment of this ambient type 0.

[0059] Fig. 6 shows the statistical information (i.e. mean, median, and standard deviation) of 68 (note: only 34 are shown in the figure for clarity purposes) samples collected for the first 4 days. From the figure, one can see the gradual decrease in the mean current of each sample with time, irrespective of RH. This is a sign that the bP chemiresistor is suffering from the effect of residual vapor adsorption on its surface. This is further illustrated in Fig. 7, i.e. that the bP chemiresistor has not recovered to its original state, as the mean currents for the same RH taken at 3 different days are different. Nevertheless, it will be shown later that these negative effects have no bearings on the test score of the machine-trained gas sensing system according to example embodiments.

[0060] **Ambient Type 1:** Variation in CO₂ only. A photograph of an experimental setup for machine training a wireless 2DM-based gas sensing system for relative humidity and CO₂

measurement is as shown in Fig. 8 (noting that the N₂O reference sensor 803 is not used, i.e. like oxygen and nitrogen, N₂O is part of the ambient air present but their concentration level is very low at around 0.00003%). In this setup, the CO₂ concentration level is controlled by flowing the CO₂ gas (purity = 99.999%) into the chamber 802 for a fixed duration of time, ranging from 5 seconds to 60 seconds, through a Mass Flow Controller 801 at a fixed rate of 5 SCCM. Once ready, the valve of the gas inlet is closed, and the CO₂ can diffuse gradually through the edges of the door on the setup. The current flowing across the bP chemiresistor during this time is then measured and recorded wirelessly on a tablet at an interval of 0.3 s for 3 mins. In addition to the measured current, the ambient temperature as well as the concentration levels, from the reference CO₂ and the RH sensors 804, 806, respectively, are also recorded, once at the start of the 3-mins current measurement and then again at the end of the 3-min measurement. The variations in the concentration levels, ambient temperatures and the measured current would then be passed on to the machine learning algorithm for training. Multiple set of data are collected at ambient condition across a wide range of CO₂ concentration levels (e.g. 544 ppm to 1909 ppm). The experiment is conducted across 2 months and the number of sample files collected for CO₂ and relative humidity are 642 (i.e. sample size = 642) with each sample containing 600 measurement points.

[0061] It is noted that the sensor is trained according to this example embodiment in ambient condition, where ambient means RH is present in the environment. Since H₂O/RH is one of the gases the sensor is trained to measure, its relatively constant concentration level is being recorded to train the model to spot the difference in the conductivity between the situations when only CO₂ is changing and when RH is changing. Both RH and CO₂ can each cause a change in the conductivity of the chemiresistor. By varying only one component at a time and keeping the other(s) present but constant, one can train the sensor according to example embodiments to do concentration prediction for multiple gases/VOCs. This advantageously overcomes the difficulties in predicting multiple gases from a single overall incremental change in the conductivity of the chemiresistor when it is exposed under multiple sources of gases/VOCs.

[0062] **Ambient Type 2:** Variation in CO₂ and N₂O. The experimental setup is as shown in Fig. 8. In this case, the N₂O concentration (obtained from the N₂O reference gas measuring sensor 803) is controlled by flowing the N₂O gas (purity = 99.999%) into the chamber 802 for a fixed duration of time, ranging from 5 seconds to 60 seconds, through the Mass Flow Controller 801 at a fixed rate of 5 SCCM. Once ready, the valve of the gas inlet is closed and the CO₂ is allowed to diffuse gradually through the edges of the door on the setup. The current

flowing across the bP chemiresistor during this time is then measured and recorded wirelessly on our tablet at an interval of 0.3 s for 3 mins. In addition to the measured current, ambient temperature as well as the concentration levels from the reference N₂O, CO₂ and the RH meters, respectively, are also recorded, once at the start of the 3-mins current measurement and then again at the end of the 3-min measurement. The variations in the concentration levels, ambient temperatures on the CO₂ sensor 804 and RH sensor 803 (N₂O sensor 803 has no ambient temperature reading) and the measured current would then be passed on to the machine learning algorithm for training. Multiple set of data are collected at ambient condition across a wide range of CO₂ concentration levels (e.g. 27 ppm to 874 ppm) and N₂O concentration levels (e.g. 19 ppm to 945 ppm). The experiment is conducted across 2 months and the number of sample files collected for CO₂ and N₂O are 586 (i.e. sample size = 586) with each sample containing 600 measurement points.

[0063] **Data Collection for VOCs detection via Machine Learning N=2: CO₂ and RH (E.g. Ambient type0=Empty container with no plant, type1=Non-aromatic plant only, and type2=Aromatic Plant which emit VOCs) according to an example embodiment.**

[0064] Fig. 9 shows the experimental setup for classifying VOCs emitted by plants. The aromatic plant is a Basil plant and it is known in the literature that they emit the following VOCs

- [0065] 1. α -pinene,
- [0066] 2. β -pinene,
- [0067] 3. Eucalyptol,
- [0068] 4. linalyl acetate, phenylpropene
- [0069] 5. Eugenol, and sesquiterpene,
- [0070] 6. α -bermagotene,
- [0071] 7. germacrene-D,
- [0072] 8. γ -muurolene,
- [0073] 9. β -copaene.

[0074] The gases that were actively monitored for change in the experiment according to this example embodiment are CO₂ and RH only. It is noted that if it is desired to not only classify the ambient type, i.e. the presence of the emitted VOCs, but also to predict the concentration level of each individual VOC emitted by the Basil plant, one would additionally obtain the reference concentration value(s) of each VOCs for regression training. However, in

this VOC detection example embodiment, the intention is to provide a proof of concept that example embodiments of the present invention can also be sensitive to VOCs.

[0075] The data collection and training methodology in embodiments in which the concentration level of each individual VOC is predicted will be the same as described with reference to in Figs. 5 and 10 herein for a multi-gas environment. Similar to e.g. CO₂ or RH, VOCs also consists of molecules in the gas state except one is organic in nature while the other is inorganic (i.e. CO₂). Having demonstrated that an example embodiment responds to this type of vapour, the same ML technique can be applied, and a similar prediction accuracy can be expected, as will be appreciated by a person skilled in the art.

[0076] **Training the Wireless Chemiresistor for Multi-gas sensing via Machine Learning according to example embodiments**

[0077] In the data files collected during the data collection, time series of the measured current across the chemiresistor, respective concentration levels and ambient temperature taken from the reference sensors, the collection date and time and the gas types are available. Using this information, a computer program (e.g. based in Python language) can be written to create the AI models for each gas/VOCs type and use them for prediction. Fig. 10 illustrates the process of training a single 2DM-based chemiresistor via machine learning (ML) for classifying and quantifying multiple sources of gases/VOCs that are present simultaneously in the same environment, according to an example embodiment.

[0078] Specifically, indicated as step 1, the training and testing data collection is performed as described above with reference to Figure 5. Indicated as step 2, Fourier Transform is applied to the various collected time domain/series electrical responses of the 2DM-based chemiresistor to obtain the low frequency noise profile of the exposure and locate the Lorentzian components associated in it. From the noise profiles, all required input features are computed. Altogether 15 features were used according to the example embodiments described herein:

- [0079] 1. Rch(ohm)
- [0080] 2. RunTime(s)
- [0081] 3. AmbientTemp(C)
- [0082] 4. RchSignatureFreq(Hz)
- [0083] 5. RchMaxLorentzPSD(1/Hz)
- [0084] 6. RchSignatureDesorption(s)
- [0085] 7. RchKurtpLorentzPSD
- [0086] 8. RchSkewpLorentzPSD

[0087] 9. RchMaxLorentzPSDmedian(1/Hz)

[0088] 10. RchMaxLorentzPSDratio

[0089] 11. nLorentzPSDPeaks

[0090] 12. MedianPSDPeaks(1/Hz)

[0091] 13. MedianfreqPeaks(Hz)

[0092] 14. FWHMmaxHz(Hz)

[0093] 15. FWFmaxHz(Hz)

[0094] As will be appreciated by a person skilled in the art the above features contain information such as:

[0095] the time dependent electrical responses (i.e. channel resistance) from a single 2DM-based chemiresistor. i.e. feature 1 above

[0096] the operating conditions such as the ambient temperature and run time. i.e. features 2 & 3 above

[0097] its derivatives such as the characteristic Lorentzian frequencies (i.e. peaks with the maximum power spectral density) and their respective power spectral density from the plot of noise spectral density multiplied by frequency vs frequency (i.e. Lorentzian noise spectral). i.e. features 4 & 5

[0098] the characteristic Lorentzian desorption time (i.e. the inverse of the Lorentzian characteristic frequency), i.e. feature 6

[0099] the Kurt, Skew, median of the Lorentzian noise spectral. i.e. features 7, 8 & 9

[00100] the power spectral density ratio of the characteristic Lorentzian frequency to the median of the Lorentzian noise spectral, i.e. feature 10.

[00101] the numbers of Lorentzian Peaks found in the Lorentzian noise spectral, the median of these peaks and the frequencies associated to these peaks, i.e. features 11, 12 & 13.

[00102] the full width half maximum and full width full maximum of the characteristic Lorentzian peak (i.e. the peak with the highest power spectral density), i.e. features 14 & 15.

[00103] Indicated as step 3a, using the measured channel resistance time series, their Lorentzian derivatives and the operating conditions as input features and all the associated type of ambient environments as target labels, train a classification model with any established ML algorithm (e.g. from scikit-learn) to predict the type of ambient environment from the input features. Repeat step 1 if the accuracy is not satisfactory.

[00104] Indicated as step 3b, once classification modelling is completed, categorize each set of input features according to their classification label (i.e. ambient type). Then train a regression model for every ambient type with any established ML algorithm using feature set

with the same ambient type as inputs and their associated concentration levels as target values. The number of trained regression models should be equal to the number of ambient types. Repeat step 1 if the accuracy is not satisfactory.

[00105] It is noted that even though the data collection in the above described specific example embodiments do not include the full spectrum of all the ambient conditions specified according to a preferred embodiment as described above with reference to Fig. 5, from the result achieved from all the specified ambient conditions (although incomplete) one can deduce that for a 3-gases sensor according to a preferred embodiment that covers all the desired operating conditions, it is preferably trained as described with reference to Fig. 5 above, as will be appreciated by a person skilled in the art.

[00106] Similarly, it will be appreciated by a person skilled in the art that it is not necessary to have demonstrated a sensor according to example embodiments using various different 2D materials to deduce that embodiments of the present invention can generally work for various 2D materials sharing the same general properties as the ones described in the specific embodiments herein.

[00107] The training methodology according to example embodiments of the present invention is very versatile as it depends on how the sensor would be used. E.g. if a user knows for certain the operating conditions would not experience any change in one gas/VOC, e.g. RH, then one can eliminate the variation cycle for RH in the training loop and still use the sensor. That is, the accuracy of the prediction is to be considered together with the associated ambient condition it is trained under. For example, a particular prediction accuracy can be valid for an ambient where CO₂ is changing but RH and N₂O are assumed to be constant, as shown in Figure 16, which will be described in more detail below.

[00108] If a user is not satisfied with such an operating condition the training loop described with reference to Fig. 5 can be continued/completed to obtain a 3-gases sensor that can operate under all operating conditions according to a preferred embodiment, be it whether 1, 2, or 3 gases are simultaneously changing or not.

[00109] **Deployment of trained classification and regression models for Multi-gas/VOCs sensing according to an example embodiment**

[00110] Fig. 11 shows the signal flow diagram illustrating prediction for Multi-gas/VOCs sensing according to an example embodiment. Indicated at numeral 1200, the 2DM chemiresistor is exposed in an environment with multiple sources of gas/VOCs. Indicated at numeral 1202, the channel resistance is recorded at an interval of 0.3 seconds for 3 minutes and the measured time series data is used to create the required input features (compare

classification modelling described above with reference to Figure 10). Indicated at numeral 1204, the trained classification model is applied to determine the corresponding ambient type from the input features and reveal what types of gas/VOCs are present. Indicated at numeral 1206, the concentration level of each gas/VOCs type is then predicted by the respective trained regression models for the determined ambient type (compare regression modelling described above with reference to Figure 10).

[00111] System implementation of a gas sensor or gas sensing node according to an example embodiment

[00112] Fig. 12 describes briefly the system implementation block-diagram of an all-in-one gas sensor 900 according to an example embodiment as an air quality sensor in a standalone consumer product for tracking health or as a climate monitoring sensing node in a wireless sensor network for production control in a factory or industrial safety application. The computation of the output (indicated at block 902) can either be done on a mobile device(s) or via the Cloud for more automation and complex data analytic computation. Specifically, block 904 indicates that the gases steal/donate electrons which in turn results in changes on the resistance, indicated as block 906. In an example embodiment, data representing the change in resistance is wirelessly transmitted to a mobile device(s)/the Cloud, indicated as block 902. Data representing the computed statistics and other rates of change (indicated at block 908), are transmitted (e.g. wirelessly) to the A.I. model block 910 of the all-in-one gas sensor 900, for making a prediction of the gas type and concentration level, indicated at block 912.

[00113] Results and analysis according to an example embodiment

[00114] The results in Fig. 13 shows the characteristic Lorentzian frequencies and associated statistical information (compare also feature list described above with reference to Fig. 10) extracted from 3 different ambient environments (namely type 0, 1, and 2 described above for an example embodiment) and can be seen as the first proof of principle for using characteristic Lorentzian frequencies to distinguish multiple gases from a single 2DM-based chemiresistor according to an example embodiment, in this case, RH, CO₂, and N₂O. Similarly, Fig. 14 shows the characteristic Lorentzian frequencies and associated statistical information (compare also feature list described above with reference to Fig. 10) extracted from 3 other different ambient environments of another ambient type-0, where there is no plant in the enclosure, another ambient type-1 where there is a plant that is known to not emit any VOCs in the enclosure, and finally another ambient type-2 where there is a plant that is known to emit strong VOCs in the enclosure (compare Figure 9 and corresponding description above), according to an example

embodiment. The results can be seen as the first proof of principle for using characteristic Lorentzian frequencies to distinguish plants in distress based on their VOCs emission.

[00115] The results in Fig. 15, Fig. 16, and Fig. 17, show the prediction accuracy of an all-in-one sensor according to an example embodiment for RH (test score =0.998935), CO₂ (test score =0.999999) and N₂O (test score =0.999998) gas. The test scores are all based on the support vector machine regression (SVR) and decision tree classification algorithms (test score = 0.999243), as is understood in the art. The results show that the same physical sensor according to an example embodiment can advantageously be used to simultaneously detect three types of gases, RH, CO₂ and N₂O gas, and their concentration level in a dynamic fashion (i.e. the gases need not be in steady concentration state) within a controlled environment. Specifically, in Fig. 15 the predicted RH by support vector machine regression (data points) versus actual RH (curve) are shown, with a response time = 1.5 mins. The RH training and testing was conducted while the CO₂ gas concentration is decreasing at the same time. It is noted that the sensor was trained under ambient condition which also include the presence of O₂, N₂ and N₂O. Since no sources of O₂, N₂, and N₂O were introduced, they are assumed to be constant under the experimental conditions (which is a controlled environment). In Fig. 16, the predicted CO₂ by support vector machine regression (data points e.g.) vs actual CO₂ (curve) are shown. The CO₂ training and testing was conducted while the N₂O gas concentration is decreasing at the same time albeit at a slower rate than CO₂, at a relatively constant RH. The response time =1.5 mins. In Fig. 17, the predicted N₂O by support vector machine regression (data points e.g.) vs actual N₂O (curve) are shown. The N₂O training and testing was conducted while CO₂ gas concentration is dropping at the same time albeit at a faster rate than N₂O, at a relatively constant RH. The response time =1.5 mins.

[00116] An all-in-one sensor based on 2DMs for relative humidity (RH), carbon dioxide (CO₂) and nitrogen oxide (N₂O) has been provided according to example embodiments. The ML training according to example embodiments achieves a test score above 99.8% for all three gases with a response time of 1.5 mins. This implies that at least 99.8% of the variability in the dependent variable has been accounted for by all the dedicated AI engines. According to example embodiments, not only can a single physical sensor that is sensitive to a broad spectrum of gases be functionalized to selectively detect RH, CO₂ and N₂O via machine learning, a lower power consumption (25 mV and < 10 uA) with long shelf life and small physical size can advantageously be achieved as well with the use of a two-dimensional material. By furthering the training with other gases and vapors, an all-in-one portable sensor according to various embodiments can be provided for detecting air quality in the form of, by

way of example, volatile gases, carbon dioxide, carbon monoxide, pollen, or toxins in the air, in addition to relative humidity, oxygen and nitrogen concentration. Data can be displayed in a software application installed on a mobile device or stationary terminal with actionable feeds at a higher intelligent level for the user to act upon according to various embodiments. By producing different AI engines for different gases and vapors, new sensing capability can also be added to the all-in-one sensor according to various embodiments on demand in real time without any change in the hardware. within various embodiments, with reinforcement learning (another type of machine learning technique), calibration of the sensor can either be eliminated or reduced in frequency.

[00117] Fig. 18 summarizes the classification and regression results achieved from two different 2DM-based sensors according to example embodiments, one of which is based on black phosphorous (bP), Dev11-bP and the other is based on a Tellurene (Te), Dev01-Te. The bP-based sensor was shown to be able to classify 3 different ambient environment with 3 gases, namely RH, CO₂, and N₂O, and also quantify their respective concentration levels in the environment, while the Te-based sensor is shown to be able to classify 3 different ambient environments, one of which has no plant in it but with CO₂ rising and RH decreasing via normal diffusion through the gap of the door, one with a non-aromatic plant but with CO₂ hovering around 595-615 ppm and RH hovering between 72-74 %, and lastly, one with an aromatic plant, a CO₂ concentration that hovers around 605-615 ppm, and a RH that rises from 65% to a max of 76% before settling back to 72-73%.

[00118] Figure 19 shows a flow chart 1900 illustrating a computerized method of determining respective presence and concentrations of multiple gases and/or volatile organic compounds, according to an example embodiment. At step 1902, one or more sensing elements with the same chemical and physical properties are exposed to the multiple gases and/or volatile organic compounds. At step 1904, electrical time series data of the one or more sensing elements is measured during the exposure. At step 1906, the electrical time series data and Lorentzian noise information of the electrical time series data is analyzed by an Artificial Intelligence (AI) system. At step 1908, the respective presence and/or concentrations of the multiple gases and/or volatile organic compounds are determined based on the analysis of the electrical time series data and the Lorentzian noise information of the electrical time series data.

[00119] The method may further comprise analyzing an ambient temperature by the Artificial Intelligence (AI) system and determining the respective presence and/or

concentrations of the multiple gases and/or volatile organic compounds is further based on the analysis of the ambient temperature.

[00120] The Lorentzian information may comprise features selected from a group consisting of the characteristic Lorentzian peak with the maximum power spectral density, their respective power spectral density, the characteristic Lorentzian desorption time the Kurt, Skew, median of the Lorentzian noise spectral, the power spectral density ratio of the characteristic Lorentzian frequency to the median of the Lorentzian noise spectral, the numbers of Lorentzian peaks found in the Lorentzian noise spectral, the median of the Lorentzian peaks, the frequencies associated to the Lorentzian peaks, the full width half maximum and full width full maximum of the characteristic Lorentzian peak.

[00121] The AI system may be a classification or regression model AI system or a reinforcement learning AI system.

Each sensing element may comprise a two-dimensional sensing material. The two-dimensional sensing material may be configured as a chemiresistor and the electrical time series data may comprise resistance time series data. The two-dimensional sensing material may comprise one or a group consisting of black Phosphorous (bP), Tellurene, reduced graphene oxide, graphene, and Transition metal dichalcogenides, or any two-dimensional allotropes of various elements or compounds with a carrier mobilities that are comparable to black Phosphorous for low-power operation.

[00122] Figure 20 shows a schematic diagram illustrating a sensor device 2000 capable of determining respective presence and concentrations of multiple gases and/or volatile organic compounds, according to an example embodiment. The sensor device 2000 comprises one or more sensing elements 2002 with the same chemical and physical properties and an Artificial Intelligence (AI) system 2004, wherein the AI system 2004 is configured to analyze the electrical time series data and Lorentzian noise information of electrical time series data and to determine the respective presence and/or concentrations of multiple gases and/or volatile organic compounds based on the analysis of the electrical time series data and the Lorentzian noise information of the electrical time series data.

[00123] The AI system 2004 may further configured to analyze an ambient temperature and to determine the respective presence and/or concentrations of multiple gases and/or volatile organic compounds further based on the analysis of the ambient temperature.

[00124] The Lorentzian information may comprise features selected from a group consisting of the characteristic Lorentzian peak with the maximum power spectral density, their respective power spectral density, the characteristic Lorentzian desorption time the Kurt, Skew, median

of the Lorentzian noise spectral, the power spectral density ratio of the characteristic Lorentzian frequency to the median of the Lorentzian noise spectral, the numbers of Lorentzian peaks found in the Lorentzian noise spectral, the median of the Lorentzian peaks, the frequencies associated to the Lorentzian peaks, the full width half maximum and full width full maximum of the characteristic Lorentzian peak.

[00125] The AI system 2004 may be a classification or regression model AI system or a reinforcement learning AI system.

Each sensing element may comprise a two-dimensional sensing material. The two-dimensional sensing material may be configured as a chemiresistor and the electrical time series data may comprise resistance time series data. The two-dimensional sensing material may comprise one or a group consisting of black Phosphorous (bP), Tellurene, reduced graphene oxide, graphene, and Transition metal dichalcogenides, or any two-dimensional allotropes of various elements or compounds with a carrier mobilities that are comparable to black Phosphorous for low-power operation.

[00126] In one embodiment, a method of training a sensor device of the embodiments described above with reference to Fig. 20 to be capable of determining respective presence and concentrations of multiple gases and/or volatile organic compounds is provided.

[00127] The method may comprise data collections steps of i) exposing the one or more sensing elements to a desired number and type of gases and/or volatile organic compounds in a controlled environment and measuring a first dataset of the electrical time series data; ii) varying a concentration of one of the gases and/or volatile organic compounds and measuring a second dataset of the electrical time series data; and iii) repeating step ii) over a desired range of concentrations.

[00128] The method may further comprise data collection steps of iv) varying respective concentrations of two of the gases and/or volatile organic compounds and measuring a further dataset of the electrical time series data; and v) repeating step iv) over a desired ranges of combinations of respective concentrations of the two of the gases and/or volatile organic compounds.

[00129] The method may further comprise data collection steps of vi) repeating steps iv) and v), wherein in each repetition, an additional one of the gases and/or volatile organic compounds is added in steps iv) and v).

[00130] The method may further comprise performing machine training on the datasets collected in the data collection steps. Performing the machine learning may comprise training a classification model to predict the number and type of gases and/or volatile organic

compounds, and training a regression model to predict the respective concentrations of the gases and/or volatile organic compounds.

[00131] Embodiments of the present invention can have one or more of the following features and associated benefits/advantages:

Feature	Benefit/Advantage
Embodiments of the present invention use only a single physical chemiresistor or an array of chemiresistors of the same chemical and physical composition to simultaneously detect the presence and quantify the concentration of multiple types of gases/VOCs. More specifically, 1. There are no multiple physical discrete sensors assembled on a PCB board, each of which uniquely catered to different gas/VOCs types. Or 2. There are no coatings applied or nano-particles added or chemical modification carried out to our sensing material to achieve the sensing of multiple types of gases/VOCs.	1. Lower electrical power consumption as there will only be a single interface circuit required. 2. Smaller in size. 3. Easier to maintain in terms calibration and replacement. 4. Lower fabrication cost as no functionalization is needed. 5. Ready for deployment on an internet of Things (IoT) platform as it is small size, low power, low cost & low maintenance.
The sensing material used in the chemiresistor according to example embodiments of the present invention is a two-dimensional inorganic layered material (2DMs) that is highly sensitive to a broad variety of gases and VOCs.	1. improves detection sensitivity and thus accuracy due to the two-dimensionality of the material structure. 2. Due to the two-dimensional structure, the material is highly sensitivity to surface disturbances from any gases or VOCs that lands on its surface. 3. reduces recovery time (i.e. gas desorption time) as no covalent bonds are formed with the analyte. 4. eliminates the need to heat-up the sensor.
The sensing material used in the chemiresistor according to example embodiments of the present invention is a two-dimensional layered inorganic material (2DMs) that has high carrier mobility.	1. lower the power consumption of the sensor as the higher carrier mobility in the 2DMs increases the conductivity of the chemiresistor and therefore a lower bias voltage

	can be used (e.g. to less than 25 mV).
According to example embodiments of the present invention, Gas or VOCs discrimination is functionalized through respective AI models (i.e. AI Engines) developed by exhaustive machine-learning (ML) in real environment settings.	1. Allows multiple gases or VOCs to be classified and quantified simultaneously from a single physical chemiresistor. 2. Allows real-time on demand upgrades with expandable detection range & type 3. Allows customization of sensing needs and applications. 4. New sensing capabilities can be added on demand in real-time without any change in the physical hardware by installing additional AI engines to the software applications. 5. Allows continuous Improvement in accuracy and thus calibration-free. 6. Remove the need to have multiple physically distinctive sensors for detecting multiple gases or VOCs.

[00132] Embodiments of the present invention have application as gas sensors, for example as an air quality sensor in a standalone consumer product for tracking health or as a climate monitoring sensing node in a wireless sensor network for production control in a factory or industrial safety application. A gas sensor is a device that can detect the presence and quantify the concentration of a specific gas in the atmosphere such as water vapor (humidity), organic vapors and hazardous gases. They are widely employed in environmental monitoring and emission control, personal and military safety, production control in agriculture and industry and medical diagnostics.

[00133] However, conventional gas sensors are designed to detect only a single type of gases or vapors. So, in a wireless sensor network where multiple gases or vapors needs to be monitored, sensing node build with conventional sensors will be bulky, as multiple unique gas sensors are needed in the circuit, and have high power consumption and maintenance cost, as multiple unique read-out circuits & calibrations are required for the sensing node!

[00134] Since embodiments of the present invention use just one physical sensor to acquire the footprints of all gases, the wireless sensor node is small (i.e. thumb-size) and can last more

than, for example, 12 months on a 3V lithium button cell battery. The AI models developed for the sensor according to example embodiments can also be used to eliminate physical calibration requirement or reduce the calibration frequency, e.g. by using reinforcement learning.

[00135] The various functions or processes disclosed herein may be described as data and/or instructions embodied in various computer-readable media, in terms of their behavioral, register transfer, logic component, transistor, layout geometries, and/or other characteristics. Computer-readable media in which such formatted data and/or instructions may be embodied include, but are not limited to, non-volatile storage media in various forms (e.g., optical, magnetic or semiconductor storage media) and carrier waves that may be used to transfer such formatted data and/or instructions through wireless, optical, or wired signaling media or any combination thereof. Examples of transfers of such formatted data and/or instructions by carrier waves include, but are not limited to, transfers (uploads, downloads, e-mail, etc.) over the internet and/or other computer networks via one or more data transfer protocols (e.g., HTTP, FTP, SMTP, etc.). When received within a computer system via one or more computer-readable media, such data and/or instruction-based expressions of components and/or processes under the system described may be processed by a processing entity (e.g., one or more processors) within the computer system in conjunction with execution of one or more other computer programs.

[00136] Aspects of the systems and methods described herein, such as the data collection, the machine learning, and the AI sensor output generation, may be implemented as functionality programmed into any of a variety of circuitry, including programmable logic devices (PLDs), such as field programmable gate arrays (FPGAs), programmable array logic (PAL) devices, electrically programmable logic and memory devices and standard cell-based devices, as well as application specific integrated circuits (ASICs). Some other possibilities for implementing aspects of the system include: microcontrollers with memory (such as electronically erasable programmable read only memory (EEPROM)), embedded microprocessors, firmware, software, etc. Furthermore, aspects of the system may be embodied in microprocessors having software-based circuit emulation, discrete logic (sequential and combinatorial), custom devices, fuzzy (neural) logic, quantum devices, and hybrids of any of the above device types. Of course the underlying device technologies may be provided in a variety of component types, e.g., metal-oxide semiconductor field-effect transistor (MOSFET) technologies like complementary metal-oxide semiconductor (CMOS), bipolar technologies

like emitter-coupled logic (ECL), polymer technologies (e.g., silicon-conjugated polymer and metal-conjugated polymer-metal structures), mixed analog and digital, etc.

[00137] The above description of illustrated embodiments of the systems and methods is not intended to be exhaustive or to limit the systems and methods to the precise forms disclosed. While specific embodiments of, and examples for, the systems components and methods are described herein for illustrative purposes, various equivalent modifications are possible within the scope of the systems, components and methods, as those skilled in the relevant art will recognize. The teachings of the systems and methods provided herein can be applied to other processing systems and methods, not only for the systems and methods described above.

[00138] The elements and acts of the various embodiments described above can be combined to provide further embodiments. These and other changes can be made to the systems and methods in light of the above detailed description.

[00139] For example, while bP was used in the example embodiments described herein, other materials can be used in different embodiments, including, but not limited to, Tellurene, reduced graphene oxide, graphene, and Transition metal dichalcogenides. Preferably, the material is a two-dimensional material with high carrier mobility and large surface area-to-volume ratio, such as any two-dimensional allotropes of various elements or compounds with a carrier mobilities that are comparable to black Phosphorous for low-power operation.

[00140] In general, in the following claims, the terms used should not be construed to limit the systems and methods to the specific embodiments disclosed in the specification and the claims, but should be construed to include all processing systems that operate under the claims. Accordingly, the systems and methods are not limited by the disclosure, but instead the scope of the systems and methods is to be determined entirely by the claims.

[00141] Unless the context clearly requires otherwise, throughout the description and the claims, the words "comprise," "comprising," and the like are to be construed in an inclusive sense as opposed to an exclusive or exhaustive sense; that is to say, in a sense of "including, but not limited to." Words using the singular or plural number also include the plural or singular number respectively. Additionally, the words "herein," "hereunder," "above," "below," and words of similar import refer to this application as a whole and not to any particular portions of this application. When the word "or" is used in reference to a list of two or more items, that word covers all of the following interpretations of the word: any of the items in the list, all of the items in the list and any combination of the items in the list.